Land Use Land Cover and Land Surface Temperature: Variations in the Rapidly Expanding Urban Area of Bengaluru, India

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Abstract

Land Use Land Cover (LULC) changes in urban areas have been a global phenomenon over the past few decades, and it has been even more prominent and intense in Asian counties like India. Unplanned LULC changes in densely populated urban areas can lead to ecological disturbances like increased UHI, increased frequency and intensity of precipitation, poor air quality, increased pollution levels and many more.

This study examines the temporal LULC changes and corresponding Land Surface Temperature (LST) for Bengaluru, India, between 2013 and 2021. LULC mapping for the study area indicated an increase in urban areas between 2013 and 2021, while the vegetation and the open regions declined. The mean temperature over built-up areas and open land had increased considerably, with an increase of over 60 C in mean LST temperatures between 2013 and 2021. LST over water bodies remained relatively similar, with a reduction in standard deviation indicating the homogeneity of temperatures. Spatial indicators like Normalized Difference Vegetative Index (NDVI) and Normalized Difference Built Index (NDBI) are calculated. While NDVI exhibited a negative relationship with LST, NDBI displayed a positive relationship with LST.

The results from this study highlight the need for planned growth of urban areas with sustained growth in vegetated areas through urban planning and design strategies, which can help reduce LST in future scenarios.

Keywords: LULC, LST, Spatial indicators, NDVI, NDBI.

Introduction

Urbanization is on the rise across the globe. An estimated 66% of the World's population will be living in urban areas by 2050, of which about 37% of the global urban growth is projected in India, China, and Nigeria (UNDESA, 2014). As per the UN report, 55% of the total population lives in urban areas, which is projected to be 68% by 2050. Over 404 million more urban dwellers would be added to the current urban population in India alone. The massive influx of people migrating to urban areas results in the economic exploitation of natural resources and changes in the Land Use Land Cover (LULC).

One of the biggest challenges of this unplanned development in urban areas is the permanent loss of green cover, open land, and increased built-up areas, thus altering the urban climate and the natural environment (Perera and Samanthilaka, 2014; Mukherjee and Singh, 2020). An increase in hard and reflective surfaces changes the physical characteristics of soil conditions, creates urban heat islands, alters microclimatic conditions, thermal comfort in buildings, and energy consumption patterns (Perera and Samanthilaka, 2014; Halder, Bandyopadhyay and Banik, 2021). Further, anthropogenic forces alter the natural land cover into paved surfaces and roads, thus increasing the impervious cover and reflecting surfaces, deteriorating the urban environmental quality (Rangari et al., 2019).

LULC changes from forests to cultivable lands and further to urban areas have a long-term impact on the urban environment apart from short-term implications (Natarajan and Radhakrishnan, 2020). Short-term effects include poor air/ water quality, ruined natural systems, poor sanitation, and increased solid waste (Kadhim, Mourshed and Bray, 2016). At the same time, long-term repercussions can lead to an increase in Land Surface Temperature (LST), the creation of Urban Heat Island (UHI), increased frequency and intensity of precipitation and making the urban communities more vulnerable to Floods (Nithila Devi et al., 2019; Zope et al., 2016). LST is one of the most critical parameters in assessing urban climate and the quality of the urban environment (Khan, 2021). Horizontal and vertical expansion of buildings, space between buildings, and increasing grey infrastructure in urban areas are key contributors to increasing the LST in urban areas (Crum and Jenerette, 2017). Vernacular buildings with open courtyards, like the Havelis, generally dissipate the heat from the courtyards creating thermal comfort within the buildings (Verma, Kamal and Brar, 2022).

Assessing spatial changes in LULC and LST is required to address the challenges of extensive urbanization (Tovivich, 2015; Fu and Weng, 2016; Naikoo et al., 2020). Owing to the importance of estimating LST for environmental studies, the application of Remote Sensing (RS) and Geographic Information Systems (GIS) in Urban Climate research has been growing since the 1970s (Qin and Karnieli, 1999). Extensive literature explains various methodologies for estimating LST using different RS data (Zhou et al., 2019).

India, being one of the fastest developing economies with increased urbanization, it is essential to have informed decision-making in urban planning scenarios for sustainable future growth. Many researchers modelled the historical changes in LULC of various cities across the globe. However, understanding the environmental impact of these LULC changes on the LST and other indices is less explored. Hence, this study aims to evaluate the impact of temporal changes in LULC on the LST and other spatial indicators. The objectives to achieve the same are i) to derive LULC and LST of the study area for two different periods (2013 and 2021) using Landsat 8 Imagery, ii) to understand the relations between different LULC and LST and other indices and their spatial distribution. The results of this study can provide important implications through science-backed information on urban planning and design decision-making and help achieve sustainable urban growth.

Literature Review

Changing LULC patterns in urban areas have been widely studied (Fu and Weng, 2016). The changes in LULC, however, have a widespread impact on the urban environment and ecological balance (Chapman and Hall, 2022). As Steensen et al. (2022) suggested, increased hard and reflective surfaces in urban areas with different thermal properties of the materials and reduced vegetation add up to the heat storage, thus increasing the temperature in urban areas. The temperature in urban areas is higher than in the surrounding peri-urban and rural areas and is validated using Remote Sensing (RS) data. RS data and Geographic Information Systems (GIS) have been vividly used to calculate the LST and measure the changes in LULC (Qin and Karnieli, 1999; Guha et al., 2018; Kumari et al., 2018). The advancements in RS has enabled a deeper understanding of the changing urban conditions and their impact on various urban issues, including an increase in LST (Qin and Karnieli, 1999; Kumari et al., 2018; Gessesse and Melesse, 2019).

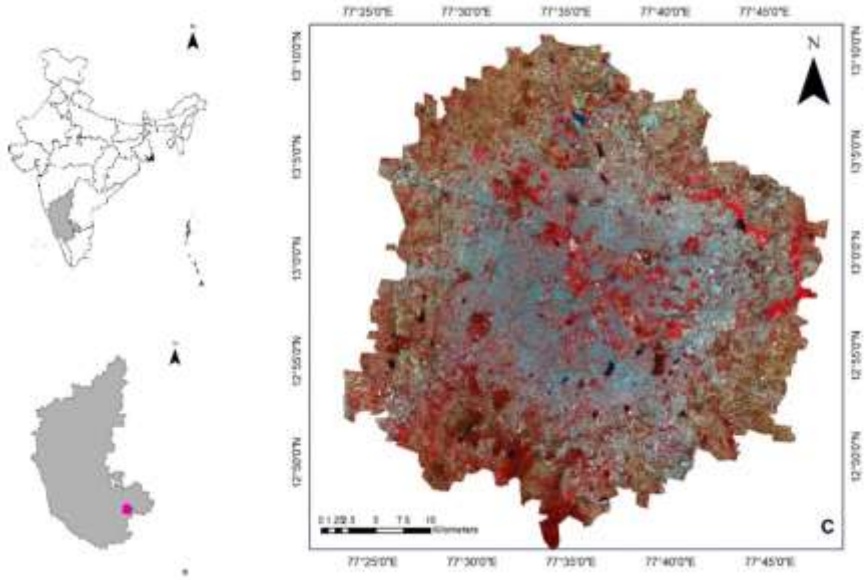

Fig. 1: Study Area Location (A) India map with state Boundaries; (B) Karnataka State Map; (C) Bengaluru (Study Area) with an FCC of Landsat 8 image of April 2021
Source: Author

Many studies have demonstrated the impact of LULC changes on the increased LST in urban areas (Fu and Weng, 2016; Das and Angadi, 2020; Mukherjee and Singh, 2020; Naikoo et al., 2020). Temporal changes in LULC have been often studied and compared with the LST. A study conducted by Sheng et al. (2017) highlighted that the value of UHI is often influenced by the selection of indicators, acquisition of data, and time and weather conditions. Data considered after a hot sunny day often produced reliable results.

In addition to the available studies on the impact of changing LULC patterns on the LST in urban areas, various indices like the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built Index (NDBI) are often considered essential indicators in understanding the changes in LST (Fatemi and Narangifard, 2019). Statistical analysis between LST and NDBI indicates a strong positive correlation explaining the increase in LST with an increase in built-up areas (Malik, Shukla, and Mishra, 2019). Various statistical analyses, including Simple Linear Regression (SLR), were conducted to explore the relationship between LST and other indices. However, Njoku (2022) highlights the need for an understanding of other spatial indicators of the changes in LST (Njoku and Tenenbaum, 2022). As highlighted by Sheng et al. (2017) and Njoku et al. (2022), there is a further need to understand the spatial implications and distribution of the changes in LST and its attributes. Hence, the need for a spatial understanding of LST distribution is emphasized.

The Study Area

Bengaluru, situated in South India, is the capital of the Indian state of Karnataka. Located in the Deccan Plateau at an altitude of about 920 M above the MSL, the city extends between 12^0 49' 55" N to 13^0 8' 32" N and 77^0 27' 29' E to 77^0 47' 2" E. Popularly known as the "Silicon city of India," it extends over 741 Sq. Km. With the surge in IT industries during the 1990s, there was a massive increase in the population. Spatially, Bengaluru expanded from 69 Sq. Km in 1901 to 741 Sq. Km in 2021. Bengaluru experienced the highest decadal growth of people (44%), significantly more compared to that of the state (31.5%) and country (31.8%) (Census of India 2011, 2011).

Bengaluru (Fig. 1) was known as a Garden city due to many Parks and Gardens developed by the 17th Century ruler Hyder Ali and later by the British. The region has an undulating topography with altitudes varying from 960 M to 740 M above MSL, allowing a well-established drainage system and interconnected storage tanks. The city enjoys a pleasant climate with 21^0 C – 34^0C in the summer and 15^0C - 25^0 C during the winter, with April being the hottest month and December being the coldest month of the year. Bengaluru receives an average annual precipitation of 800 mm and is home to rich flora and fauna (Ramachandra et al., 2017).

The massive Urban sprawl in Bengaluru over the past two decades has exerted pressure on the natural ecosystem and the development of basic infrastructures and resulted in reduced green cover, the disappearance of water bodies, altered drainage systems of natural water bodies, the UHI effect, and frequent floods. The population density of Bengaluru increased from 7881 persons/Sq. Km (2001) to 11664 persons/Sq. Km (2011) (Ramachandra et al., 2013).

Research Methodology

Data and Methods

Temporal changes in LULC of Bengaluru were studied for 2013 and 2021. Multi-Spectral Landsat Satellite Data were acquired from the United States Geological Survey's (USGS) Earth Explorer archives for the study period. The Landsat 8 Operational Land Imager (OLI) data is used for 2013 and 2021. The study period was in April, the hottest month of the year, and also to reduce the influence of seasonal variations and cloud cover. Additional details (metadata) regarding the images were retrieved from the USGS repository.

Table 1: Metadata of the Landsat Images used for the study

Source: Metadata, LS8 Data (USGS)

Source	Acquired Date (YYYY-MM-DD)	Acquired Time	Sensor ID	Cloud Cover	Spatial Resolution	Path/Row
Landsat 8	2021-04-19	05:10:31.9099799Z (GMT)	OLI_TIRS	0.89	30 x 30M	144/051
Landsat 8	2013-04-13	05:12:40.2106450Z (GMT)	OLI_TIRS	3.47%	30 x 30M	144/051

LULC Classification and Change Detection

The image classification tool in Arc GIS 10.8 is used to classify the LULC map due to its straightforward approach and high accuracy. The images are classified using the spectral signatures provided through training samples. All the images were initially stacked and processed using Composite Bands in the Image Processing Tool for preparing the LULC maps. Using the Training Sample Manager tool, training samples for four land use types: Urban, Green, Open Land/ Agriculture, and Water were selected randomly across the image. 5139 and 4742 training samples were selected for 2013 and 2021, respectively. In Landsat, 8 Bands 1-7 are used for image classification, and Bands 10 & 11 represent the Thermal bands.

Accuracy Assessment

Error Matrix, popularly known as the Confusion Matrix is used to assess the accuracy levels of the image classification. It is often used to describe the performance of a classification tool using a set of test pixels for which the actual values are known (Maps & GIS, 2016). A total of 160 samples were discreetly collected from the Landsat 8 image for the four classes: Urban, Green, Open Land/ Agriculture Land, and Water. The data from these selected reference points are then combined with the classified image to assess accuracy. Commission, Omission, Producers Accuracy (PA), and Users Accuracy (UA) are determined for each image. PA is the percentage of the correctly classified pixels to the total class reference points, and UA is the percentage of correctly classified pixels to the total reference points present in the class. Both PA and UA are measures of classification accuracy. Besides the above matrix, Kappa Coefficient is another adopted accuracy assessment coefficient.

Retrieval of Land Surface Temperature (LST)

QGIS uses an easy and less cumbersome semi-automatic plug-in SCP. The Plug-in requires thermal bands of the Landsat data and the corresponding metadata file (.MTL) as input to generate the LST. The LST is retrieved using Landsat 8 data, employing the thermal bands of radiometrically and geometrically corrected Earth Observation Data for 2013 & 2021 (LS 8).

Spatial Indices and Their Relation to LST

NDBI is the ratio between NIR and SWIR bands and is used to emphasize the built-up area while mitigating the effects of terrain illumination and atmospheric effects (Gessesse and Melesse, 2019). Since the impervious surfaces significantly affect LST, NDBI is considered to assess its impact on LST. NDBI is given by

$$\text{NDBI} = (\text{SWIR} - \text{NIR}) / (\text{SWIR} + \text{NIR}) \qquad (1)$$

NIR represents Near-infrared, and SWIR represents Short-Wave Infrared satellite image bands. Bands 5 and 6 from Landsat 8 (OLI) are used to derive NDBI. NDVI may be analyzed based on the radiation absorbed by the Red spectral chlorophyll and reflectance near the Infrared spectral Area of the NDVI values. NDVI is given by

$$\text{NDVI} = (\text{NIR} - \text{IR}) / (\text{NIR} + \text{IR}) \qquad (2)$$

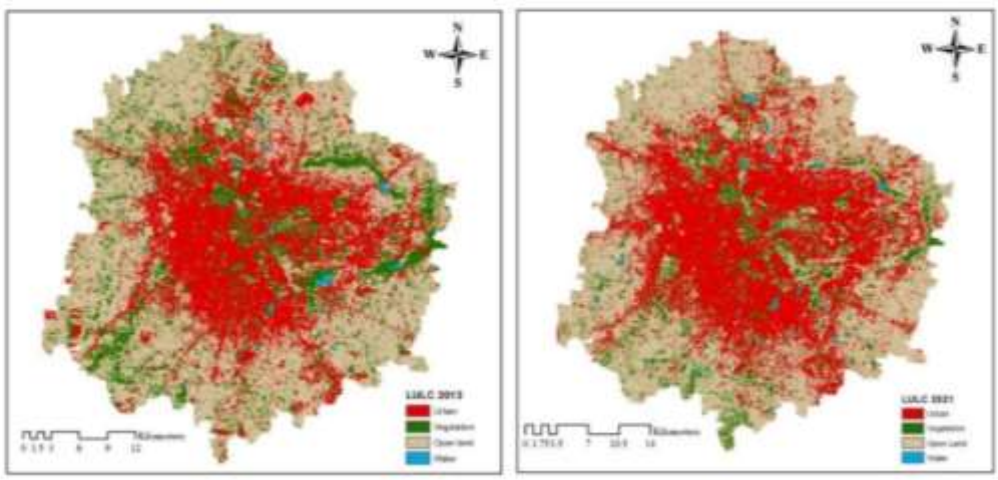

Fig. 2: LULC Map of Bengaluru for 2013, 2021
Source: Author

A Sample of NDVI, NDBI and LST Values

A fishnet is created using ArcGIS to acquire the corresponding LST values for NDVI and NDBI during the study period. Sampling points are spaced at a 500M distance through the study area, and corresponding NDVI, NDBI and LST values are extracted using the Spatial Analyst tool in ArcGIS. The grid is selected to cover the entire study area and expands over different LULCs. Over 250 samples are collected uniformly throughout the study area to maintain uniformity in the sample collection.

Table 2: LULC area distribution and change detection for 2013, 2021
Source: Author

LULC Class	2013		2021		Change detected	
	Area (km²)	Percentage	Area (km²)	Percentage	Area (km²)	Percentage
Urban	389.13	29.61	485.20	36.92	96.07	24.69
Vegetation	229.38	17.45	158.77	12.08	-70.61	-30.78
Open Land	687.99	52.35	662.38	50.40	-25.61	-3.72
Water	7.65	0.58	7.80	0.59	0.15	2.01

Findings

Land Cover Analysis

THE LULC maps of the study area for 2013 and 2021 are given in Fig. 2. The statistical results of the LULC changes for different periods (2013, 2021) are detailed in the Fig. 3.

The analysis shows a constant increase in the urban areas while there is a decline in vegetation. There was a decline in open areas from 2013 to 2021. Conversion of greenery into open lands and further into urban built-up areas is observed in the study period. There was a 24.69% increase in the built-up area between 2013 and 2021. Vegetation had declined to a greater extent paving the way for the rise in urban areas. Vegetation had dropped by 30.8% by 2021, with a net loss of 70.61 Sq. Km. The extent of water bodies has slightly increased, 2.01%, by 2021. The LULC changes across the study period are given in the Fig. 2. The positive and negative growth of different Land Use classes between 2013 and 2021 are shown in Fig. 3.

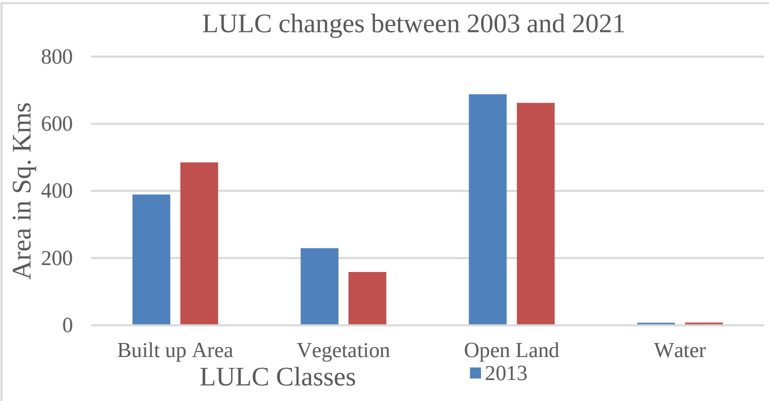

Fig. 3: LULC area changes between 2003-2013, 2013-2021, and 2003-2021
Source: Author

Accuracy Assessment of the LULC

About 160 Ground truth points are selected for each year to perform the accuracy assessment of the LULC classification. The estimated overall accuracy and Kappa value are higher than 0.90 each year. While the overall accuracy reached near perfection in 2013, the appearance of vegetation in water bodies is the possible reason for underestimating the area under water bodies during 2021. There is a 100% accuracy in classifying the vegetation in both years, and the average producer's accuracy has stood above 95%, allowing the LULC classification to be reliable for the study (Monserud and Leemans, 1992).

Table 3: Accuracy assessment of LULC classification for 2013 and 2021
Source: Author

Year	Producer's Accuracy				User's Accuracy			
	Urban	Vegetation	Open Land	Water	Urban	Vegetation	Open Land	Water
2013	97.5	100	100	100	100	100	97.5	100
2021	100	100	97.5	77.5	97.5	81.6	100	100
Average	99.16	100	95.8	91.6	95.5	93.9	97.5	100
Overall Accuracy	99.3 (2013)		93.8 (2021)					
Kappa Coefficient	0.99 (2013)		0.917(2021)					

Spatial variations in LST

With the increase in urban areas, there is an increase in the minimum temperature from 2013 to 2021. LST was calculated for the summer month of April (Fig. 4). In 2013, the minimum temperature was 16^0 C, while the observed minimum temperature increased to 24^0 C in 2021. There is a steady decrease in areas of cold and warm areas and an increase in hot and very hot areas from 2013 to 2021. About 1.6% of the area was cold (< 24^0 C) during 2013 and had decreased to 0.3% during 2021. While very hot areas (> 32^0 C) were about 15.86% in 2013, the number had come down to 8.74% in 2021. Though the maximum temperature did not significantly change, a considerable increase in the minimum temperatures from 2013 to 2021 (16^0 C and 23^0 C, respectively) resulted in a 7^0 C increase. There is a 4^0 C variation in the mean temperature from 2013 to 2021, with a standard deviation of 6.78 in 2013 and 5.05 in 2021. Over 85% of the areas fell under hot and very hot temperature zones in 2013 and 2021, exhibiting similar trends. The reduction in Standard Deviation of LST in 2021 emphasizes the homogeneity of increased temperature in 2021.

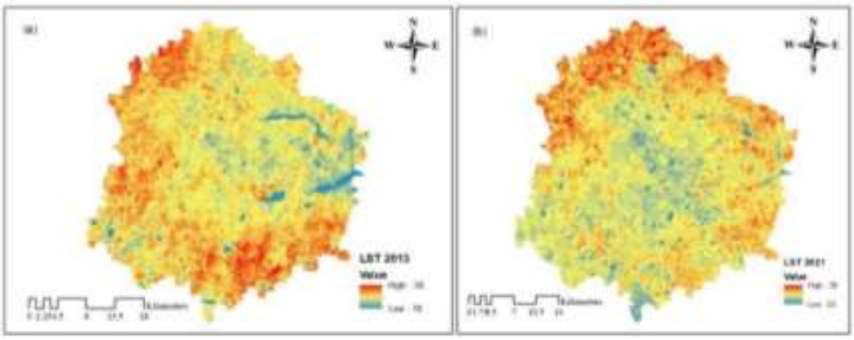

Fig. 4: LST of Bengaluru during 2013 and 2021 (a) LST Map of Bengaluru for 2013, (b) LST Map of Bengaluru for 2021
Source: Author

Table 4: LST variations between 2013 and 2021
Source: Author

Thermal Condition	Temperature	2013 (Area in Sq Km)	% of Area	2021 (Area in Sq Km)	% of area
Cold	< 24 Deg C	20.57	1.57	4.69	0.36
Warm	25-28 Deg C	174.09	13.25	204.27	15.54
Hot	29-32 Deg C	911.09	69.33	990.30	75.36
Very Hot	> 32 Deg C	208.40	15.86	114.90	8.74

LULC vs LST variations

Mean LST values for different LULC classes from urban areas were compared. Water bodies experienced the lowest mean LST during the study period, with a mean value of 27.5^0 C, which has not changed between 2013 and 2021. However, the standard deviation has reduced from 4.03 to 2.88 between 2013 and 2021. Open lands had the highest mean value of 28^0 C in 2013 and have increased to 31^0 C in 2021. The mean LST value of the built-up area was 27^0 C in 2013 and had steadily increased to 31^0C. The standard Deviation of LST values for built-up areas has reduced from 6.63 to 4.9, indicating increased temperature uniformity. Open lands also displayed a similar pattern, decreasing the standard deviation from 6.05 in 2013 to 4.8 in 2021. Vegetated areas had a mean LST value of 27^0 C during 2013 and increased to 29.5^0 C, decreasing the standard deviation from 5.4 to 4.03.

Table 5: LST Metrics for 2013 and 2021
Source: Author

Year	Minimum	Maximum	Mean	Standard Deviation
2013	16	38	27	6.78
2021	23	39	31	5.05

Association of NDVI and NDBI with LST

NDVI and NDBI

Increasing urban areas has resulted in a steady decrease in NDVI values (Fig. 5). A maximum NDVI value of 0.59 (2013) was reduced to 0.54 (2021), while the minimum NDVI value in 2013 was -0.18 and has further increased to -0.20, indicating a loss of vegetation. NDBI identifies artificial features like buildings, roads, and others. NDBI values closer to +1 show artificial features, and -1indicate natural features like water bodies, vegetation etc. A maximum NDBI value in 2013 of 0.42 has increased further to 0.51 (Fig. 5), indicating expanding urban areas. The minimum NDBI value during 2013 was -0.45, and it has further reduced to -0.42, indicating a loss of natural features.

Table 6: LULC-wise LST changes during 2013 and 2021
Source: Author

LULC Class	2013		2021	
	Mean	Standard Deviation	Mean	Standard Deviation
Built-up area	27	6.63	31	4.9
Vegetation	27	5.4	29.5	4.03
Open Lands	28	6.05	31	4.8
Water	27.4	4.03	27.5	2.88

LST vs NDVI

NDVI and LST displayed a disproportionate relation with scattered values. Maximum LST values during 2013 are grouped between 30^0 - 33^0 Deg C, with a maximum LST value appearing at NDVI at 0.18. In 2021, many values were grouped between 27^0 - 31^0 Deg C (Fig. 6), with the maximum LST value appearing at NDVI of 0.14. However, a common trend of increase is in the LST as the NDVI value decreases. With a significance *f-value* and *p-value* of 0.019 and 0.00, the relation between LST and NDVI seems to be significant.

LST vs NDBI

NDBI and LST displayed a positive relationship with a correlation coefficient of 0.67 and an r^2 value of 0.45. LST values are grouped between 29^0 C and 34^0 C, with NDBI values ranging between -0.1 and 0.12. A similar trend is observed during 2021, with maximum LST values observed between 29^0 C and 34^0 C with corresponding NDBI values ranging between -0.1 and 0.12. A maximum LST values of 37^0 C is kept at an NDBI value of 0.1 during 2013 and 2021. The tested model proves significant with significance-f and p-value standing at 0.000 and 0.000, respectively.

Conclusions

Increasing urbanization trend across the globe is posing challenges to the urban environment. Expanded built-up areas and decreased vegetation are resulting in various ecological disasters like increased LST and UHI, irregular distribution of precipitation, floods, and many more. This study emphasized the impact of changing LULC on the LST and other spatial indicators. Four LULC classes- Built-Up Area (BUA), vegetation, open lands, and water were classified for 2013 and 2021. LS 8 aided in understanding the LULC change patterns in the study area. A significant increase in BUA and reduced vegetation is observed, confirming the existing research. With expanding built-up areas, it was observed that the minimum temperature had increased by 7^0C. Also, the extent of areas with lesser temperatures had reduced, while there was an increase in the hot and very hot areas. Various indices like NDVI and NDBI also confirm the loss of natural areas and increased man-made features resulting in increased LST in less than a decade. In addition to the overall increase in temperatures, it was observed that more areas are subjected to hot and very hot conditions. The concentration of built activity in the urban areas has considerably impacted the spatial distribution of LST.

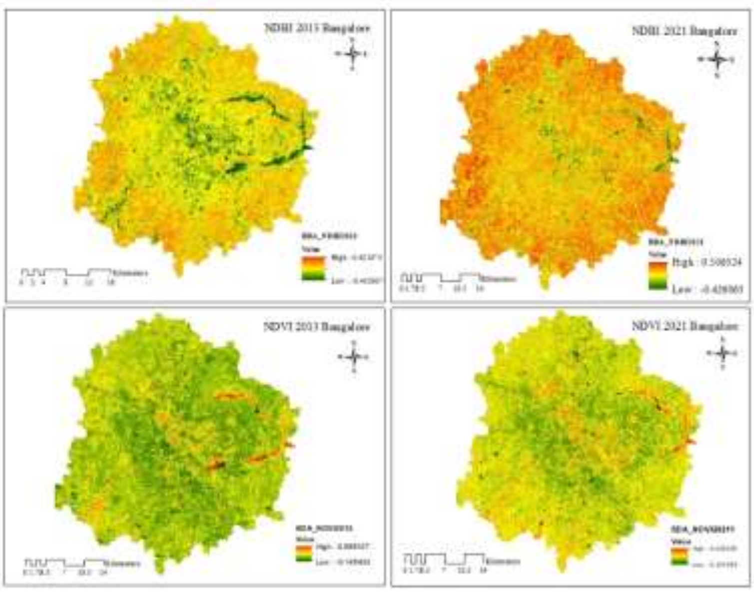

Fig. 5: NDBI and NDVI Values during 2013 and 2021 for Bengaluru, India. (a) NDBI during 2013, (b) NDBI during 2021, (c) NDVI during 2013, (d) NDVI during 2021
Source: Author

The study once again proved that vegetation plays a prominent role in limiting the increase in LST and unwanted effects like increased UHI. Local municipal authorities and government bodies need to focus on increasing green cover in urban areas by creating urban forestry, linear plantations, parks, and roof gardens. Balancing built spaces and vegetation in urban areas is essential to create environmentally sustainable and livable conditions. Efficient usage of open public land with increased green cover can further help reduce the increasing LST trend. Unplanned growth, deforestation, and de-vegetation may be catastrophic, with many unwanted effects like increased UHI, flash floods, etc. The results from this study highlight the need for the balanced growth of urban areas. Future studies could concentrate on the influence of various urban morphological parameters on LST and the impact of LST on livable conditions and energy consumption patterns in urban areas.

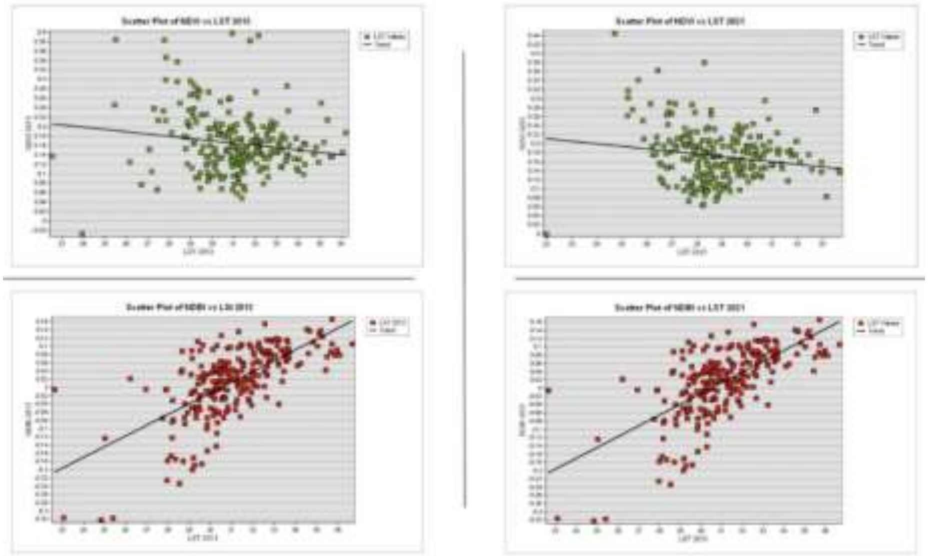

Fig.**6**: Scatter Plots depicting the correlation between NDVI and LST, NDBI and LST during 2013 and 2021 for Bengaluru, India
Source: Author

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