Assessing Land Use and Land Cover of Bengaluru Using GIS and Remote Sensing

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ABSTRACT

Land Use/Land Cover (LULC) results from a combination of natural and human factors. Understanding LULC is crucial for analyzing urban expansion, vegetation, water quality, and land suitability. Land cover changes over time can help us determine the trend in area transformation and predict its future effects. Land cover data is often obtained through remote sensing and Geographic Information Systems (GIS), with supervised classification being a common method for data analysis. Recently, Bengaluru has undergone rapid urbanization and expansion due to intense development. Due to this concentrated growth, the population has increased, straining natural resources and infrastructure and eventually giving rise to problems like climate change. Changes in land use over the past 40 years resulted in a 584% increase in built-up area and declines of 66% and 74% in vegetation and water bodies, respectively. Bengaluru's radial growth pattern indicates that urbanization is accelerating from the city's center and spreading to its outskirts. Numerous locations with higher local temperatures demonstrate the Urban Heat Island (UHI) effect. Urbanization had a significant impact on Bangalore's land temperature between 2001 and 2021, with the average temperature increasing by 0.34 degrees C per year during the highest UHI events, whereas in non-urbanized areas it increased by 0.14 degrees C per year during the same period. Increasing Land Surface Temperature (LST) will result from the decline of heat sinks such as water bodies and green cover, which will affect Bengaluru's microclimate and emphasize the importance of maintaining ecosystem services to support local communities' livelihoods. An understanding of the ecological significance of diverse habitat characteristics across the urban region is crucial for decision-makers. The research was conducted using remote sensing techniques and Landsat imagery of Bengaluru from the years 2002, 2008, 2013, 2018, and 2023. Remote sensing methods and GIS technology were used to produce LULC maps. Bengaluru's land temperature changes from 2002 to 2023 demonstrated the impact of urbanization, with an average annual temperature increase of 0.34 degrees Celsius during the highest UHI events compared to non-urbanized areas. Within the Bengaluru Metropolitan Region, the primary outcomes of this methodology are LULC and urban expansion patterns, which are considered determinants of land use change. It is projected that the outcomes will assist society and a number of organizations, including legislators and city planners.

Keywords-land use/land cover; urbanization; remote sensing; GIS; Bengaluru; BBMP boundary; maps 2002-2023

I. INTRODUCTION

A city with a large population and developed infrastructure becomes urbanized as people move from rural areas. Two-thirds of the world's population is estimated to live in cities by 2050, up from over half today [1]. Among the reasons for this urbanization trend are better access to infrastructure, educational facilities, and employment opportunities. According to the 2011 census in India, the share of the population living in cities has increased by 30% since 1901, when 11.4% of Indians lived in cities [2]. Multiple Indian cities, including Delhi, Mumbai, Kolkata, Bengaluru, and Hyderabad, have experienced rapid urban growth. The growth of metropolitan regions has numerous detrimental effects on the environment and natural resources. One major effect of urbanization is the conversion of natural landscapes into communities. The deterioration of vegetation and water bodies, which have been replaced by urban built-up areas, exacerbates environmental degradation in urban areas. Another problem the city faces is a growing population, which results in shortages of necessities such as clean air, water, and housing. The negative effects of urbanization include pollution, urban development, and the depletion of natural resources.

There are 17 Sustainable Development Goals (SDGs) that have been added to the global agenda for sustainable development by 2030. As part of SDG-13, one of the project's goals is to establish sustainable urban centers that mitigate the impacts of climate change. The 13th Sustainable Development Goal aims to enhance the capacity of national governments to plan and manage climate change effectively. This is done by including climate-related measures in their policies, strategies, and plans [3].

Most large cities have higher temperatures in their centers than in their suburbs or surrounding areas. To better understand the phenomenon, we need to understand the UHI effect. LST serves as a leading indicator of the combined impact of urban environmental, social, and morphological variables on UHI [4]. In general, these areas act as additional heat inputs to the already greenhouse-effect-driven global warming, depending on the regional climate system. The changing use of LULC is one of the most dramatic environmental changes. The study of a given region is significantly affected by annual LULC revisions. An LULC study is typically conducted to assess how vegetation and ecology in an area have changed [5]. It has been established that mapping LULC change is a crucial component of many tasks and applications, including land-use planning and global warming mitigation [6].

The use of GIS and remote sensing facilitates the analysis of changes and the drawing of logical conclusions. Data from LULC can be collected and used to benefit climatic, biogeographical, fluvial, and topographical studies. To put it another way, whereas GIS supports data collection, storage, processing, analysis, and modeling, remote sensing supports information monitoring and acquisition. Our ability to model LULC spatiotemporally can be greatly enhanced by using remote sensing and GIS. In addition to monitoring changes, it allows the prediction of upcoming changes. Using GIS and RS technologies, scientists can better understand the effects of urbanization on LULC [7]. Multiple studies have used it to monitor and simulate urban land-use patterns. Land use change analysis frequently uses RS approaches because of their temporal frequency and cost-effectiveness. Environmentalists and planners can also benefit from this technology by gaining a better understanding of the various factors influencing LULC evolution. Additionally, it might provide them with insights into the cities they intend to construct [8].

This study aims to assess how 20 years of urbanization in Bengaluru have affected land surface temperatures and other key LULC categories. Bengaluru's LULC was classified using Landsat satellite images from 2002, 2008, 2013, 2018, and 2023. The main focus is on understanding the relationship between urban growth during these years.

II. STATISTICAL ANALYSIS AND METHODOLOGY

A. *Study Area*

Bengaluru is the capital of Karnataka and the Garden City of India. The study focuses on Bengaluru's urban district. At an elevation of 921 meters, Bengaluru has a latitude of 12°58' N and a longitude of 77°35' E. Situated on the southern edge of the Deccan Plateau, the capital of Karnataka shares borders with Tamil Nadu and Andhra Pradesh, two other states in South India. Bengaluru grew from 69 square kilometers in 1901 to 712 square kilometers in 2022. According to the 2011 Census of India, Bengaluru had the highest decadal population growth (44%), substantially higher than the state's (31.5%) and the nation's (31.8%). The current estimate for Bengaluru's population in 2024 is 14,008,262. Approximately 745,999 people lived in Bengaluru in 1950. There has been an increase of 400,462 in Bangalore over the past year, representing a 2.94% annual increase. The population estimates and projections in this report are based on the most recent World Urbanization Prospects report produced by the UN. According to the World Population 2023, Bengaluru's urban agglomeration includes both the city's residents and those in nearby suburban areas.

The area's geography is undulating, with elevations ranging from 960 to 740 meters above mean sea level. This enables the installation of an advanced drainage system and linked storage tanks. The temperature ranges from 21 to 34 degrees Celsius in summer and in winter. April is one of the hottest months of the year, while December is one of the coldest. April is also one of the driest months. Over the past ten years, there have been roughly 60 wet days per year, with an average annual rainfall of about 880 mm. It is predicted that a typical summer temperature ranges from eighteen to thirty-eight degrees Celsius, while a typical winter temperature ranges from twelve to twenty-five degrees Celsius. Therefore, Bengaluru's climate makes it ideal for a healthy lifestyle year-round.

B. *Dataset and Criteria*

The urban areas of Bengaluru for the years 2002, 2008, 2013, 2018, and 2023 form the basis of the study. To understand metropolitan expansion, researchers examined the Normalized Difference Built-Up Index (NDBI). Landsat and IRS satellite imagery were used for this study. IRS data were retrieved from the Bhuvan Open Access Hub, and Landsat imagery was downloaded from Google Earth Explorer (GEE). Detailed information about the images can be found in Table I.

TABLE I. LANDSAT DATASETS USED IN THIS STUDY.

Sl. No.	Landsat image	Date	Year	Resolution(m)
1	Landsat- 7	28th March	2002	30
2	Landsat-5	27th December	2008	30
3	Landsat- 8	7th November	2013	30
4	Landsat- 8	8th January	2018	30
5	Landsat- 8	19th November	2023	30

C. *Methodology*

The LULC of the Bengaluru Metropolitan Region was categorized using GIS to compute changes between the selected years. Supervised classification was performed using six distinct sample classes: developed, water bodies (lakes, tanks), vegetation, agriculture, fallow, and others. 100 training samples were collected for each class by drawing demarcation polygons around representative sites. Each sample class was assigned a unique class ID and color to distinguish it from the others. Google Earth helped make the classification process easier by clearly identifying each pixel. A LULC change map was produced by calculating changes in LULC class area from 2002 to 2023 and expressing them in square kilometers.

D. Software Used

ArcGIS, developed by Esri, is a comprehensive GIS platform for creating, editing, and analyzing spatial data. Version 10.3 was released in December 2014.

E. Validation

The kappa coefficient assesses the accuracy of the 2023 LULC map produced by comparing it with the 2023 SVM classification map used as the reference. The kappa coefficient is calculated using the following formula (1):

$$\kappa = (p_o - p_e) \Big/ (1 - p_e) \quad (1)$$

where p_o is the observed agreement and p_e is the expected agreement by chance.

LST and Normalized Difference Vegetation Index (NDVI) vs. LST and NDBI were analyzed in 2002, 2008, 2013, 2018, and 2023. NDBI, LST, and NDVI pixels were converted into data points. A five-year analysis was conducted using 100-point NDVI, NDBI, and LST.

TABLE II. THE STUDY WAS CONDUCTED USING THE FOLLOWING LANDSAT DATA

LULC class	2002		2008		2013		2018		2023	
	Geo. area (km^2)	Area (%)	Geo. area (km^2)	Area (%)	Geo. area (km^2)	Area (%)	Geo. area (km^2)	Area (%)	Geo. area (km^2)	Area (%)
Developed	194.50	27.33	244.07	34.30	311.91	43.83	375.59	52.78	440.16	61.86
Waterbody	80.78	11.35	69.95	9.83	38.18	5.37	20.04	2.82	10.55	1.48
Vegetation	82.15	11.55	147.30	20.7	232.23	32.64	150.55	21.16	154.32	21.69
Agriculture	207.0	29.09	129.41	18.19	70.10	9.85	52.64	7.40	42.29	5.94
Fallow	6.77	0.95	8.65	1.22	5.67	0.80	20.21	2.84	14.55	2.04

III. ANALYSIS

A. Analyses of Changes in LULC

Based on the study, Bengaluru's urban area has the highest concentration of LULC classes. In Figure 1, LULC classifications are presented graphically, and in Table II, the areas classified under various LULC classes are shown as an evolution between 2002 and 2023.

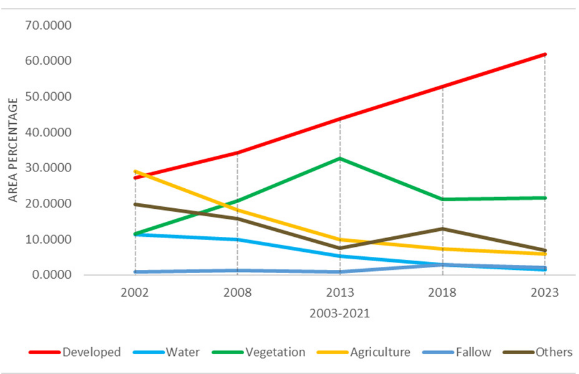

Fig. 1. An illustration of LULC's correlation from 2002 to 2023.

In 2002, the largest percentage of land was used for agriculture (29.09% of total area), with the developed class coming in second (27.33%) and vegetation 11.55% (Figure 2). In 2008, the developed class accounted for 34.30%, the water class for 9.8%, the vegetated class for 20.80%, the agricultural class for 18.18%, and the fallow class for 1.2%. The rest of the class consists of 15.7% (Figure 3).

In 2013, the developed class accounted for 43.83%, the water class for 5.36%, the vegetation class for 32.64%, agriculture for 98.5%, fallow for 0.79%, and other classes for 7.51% (Figure 4). In 2018, the developed class accounted for 52.78%, the waterbody class for 2.82%, the vegetation class for 21.16%, the agriculture class for 7.40%, the fallow class for 2.48%, and the other class for 13.01% (Figure 5). In 2023, the developed class accounted for 61.86%, the water class for 1.48%, the vegetation class for 21.69%, agriculture for 5.94%, fallow for 2.04%, and other classes for 6.99% (Figure 6). Due to the expansion of commercial and residential areas, the construction of a metro line, and the widening of the National Highway, agriculture is changing; however, the main factor driving the development of the settlement class is the increase in residential areas resulting from high demand driven by immigration.

TABLE III. FROM 2002 TO 2023, CHANGES IN LAND USE

LULC Class	2002-2023 (% change)
Developed	34.52
Waterbody	-9.87
Vegetation	10.14
Agriculture	-23.15
Fallow	1.09
Other	-12.74
Developed	34.52
Waterbody	-9.87

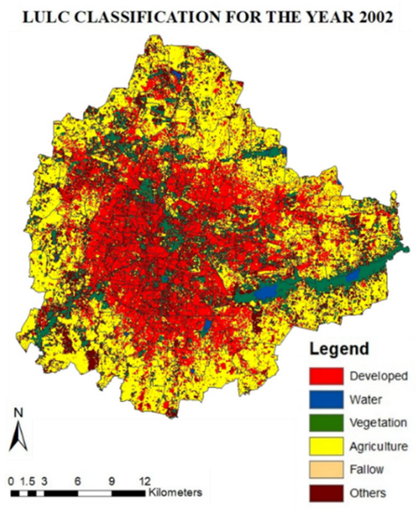

Fig. 2. LULC Classification of 2002.

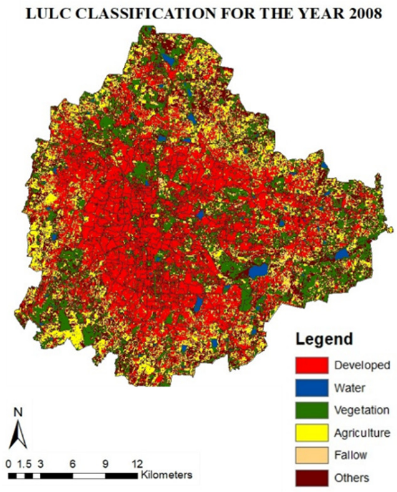

Fig. 3. LULC Classification of 2008.

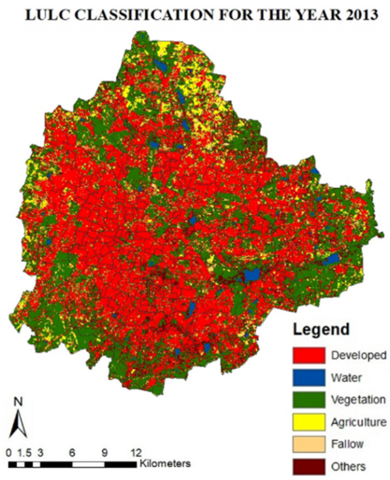

Fig. 4. LULC Classification of 2013.

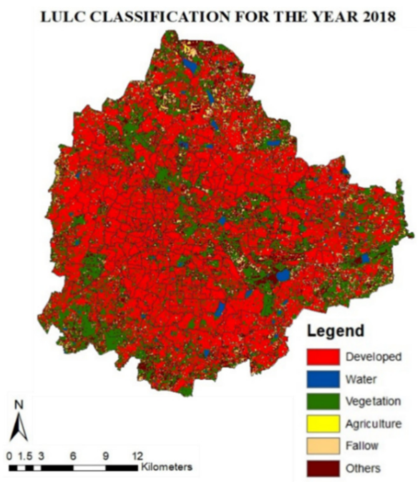

Fig. 5. LULC Classification of 2018.

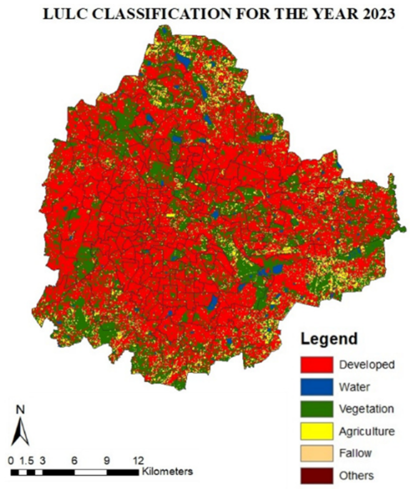

Fig. 6. LULC Classification of 2023.

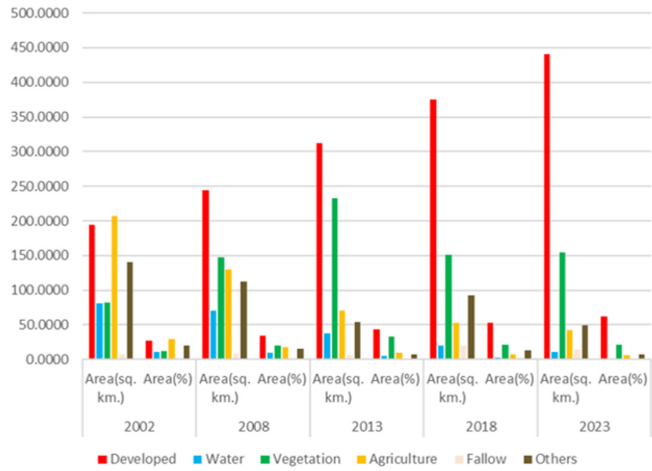

Fig. 7. Area Under Different LULC.

Figure 7 shows 27.33% less development in 2002 than in 2023, with development in 2023 being 2.5 times that of 2002. Similarly, agricultural areas decreased from 29.09% to 5.94%, and water bodies declined from 11.55% to 1.48%. Both are being transformed into settlement plots and infrastructure projects, showing a clear trend of decline.

B. Analysis of the LST

The spatiotemporal distribution of LST was analyzed using a combination of equations and Landsat thermal bands over the study period to determine its variability. There is an upward trend in the annual LST distribution between 2002 and 2023, as shown in Figures 8-12, which provide a visual interpretation of the distribution. In 2002, the maximum temperature was recorded at 30.86°C, a significant increase from 2002's 30.86°C to 2023's 37.30°C. Accordingly, the minimum temperature recorded in 2002 was 25.80 °C, which is expected to peak at 28.83 °C in 2023, which is a remarkable increase. A number of factors may have contributed to the rising trend in temperatures during the study period, underscoring their potential influence on LST dynamics [9].

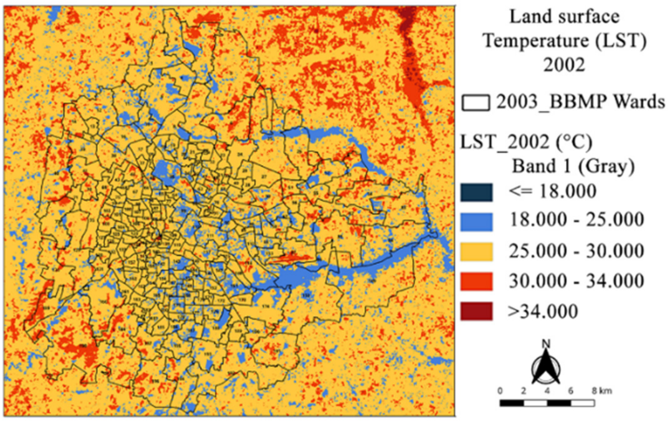

Fig. 8. LST 2002.

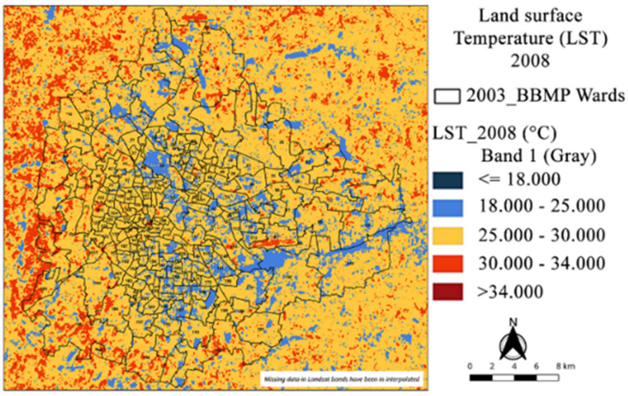

Fig. 9. LST 2008.

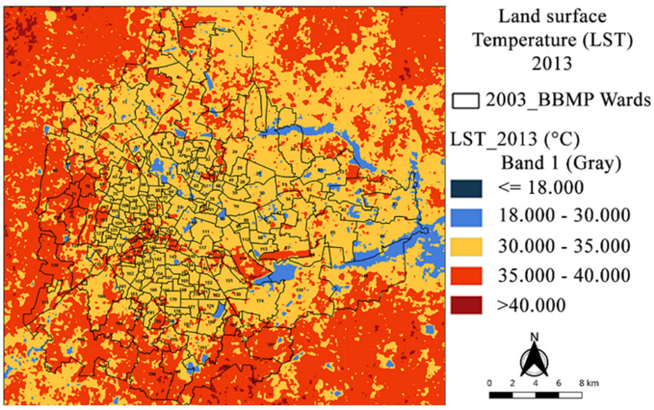

Fig. 10. LST 2013.

This data suggests a persistent rise in the mean temperature over the period 2002-2023, punctuated by a significant increase in LST. Additionally, the maximum temperatures show an upward trend, which could indicate a possible change in climate patterns.

C. LULC Indexes and Their Interactions

To identify the relationship between the two variables, the correlation coefficients (R^2) are shown in Figure 13. There are compelling patterns between the NDBI and LST for the years 2002, 2008, 2013, 2018, and 2023. There is a slight increase in the correlation coefficient between 2002 and 2023, indicating that the relationship is intensifying over time. LST and NDBI are clearly shown to have a positive relationship, regardless of the slopes or intercepts of the linear regression models for each year.

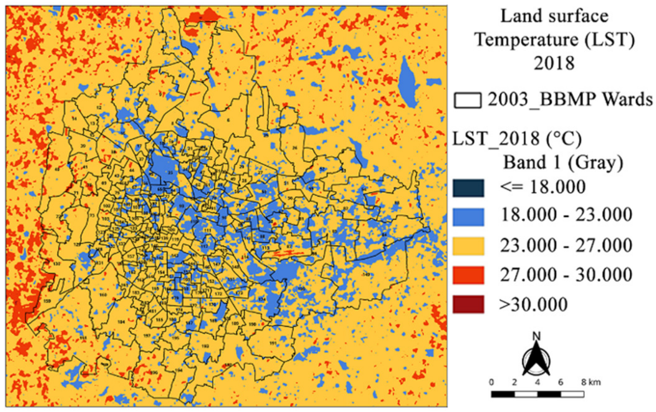

Fig. 11. LST 2018.

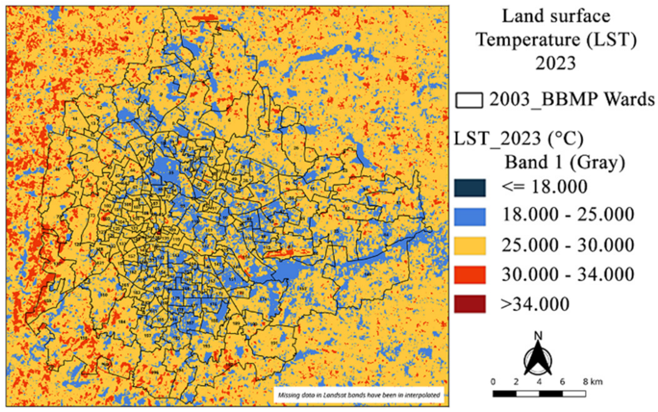

Fig. 12. LST 2023.

Study results show a positive correlation between LST and NDBI across all five years (2002, 2008, 2013, 2018, and 2023), indicating that LST increases with NDBI. The correlation coefficient for 2002 is $R^2 = 0.4666$, which means nearly 46.6% of the NDBI variability during this year can be attributed to LST, with a positive slope of 16.111x and an intercept of 23.989. With $R^2 = 0.5573$ and $R^2 = 0.5831$, there is a strong positive correlation between 2008 and 2013, where NDBI variability exerts a strong influence of 55.73% and 58.31%, respectively, on LST, with a slope of 26.016x and an intercept of 20.971 in 2008 and a slope of 29.986x and an intercept of 26.625 in 2013. With NDBI variability of 25.48% and 12.88%, respectively, 2018 and 2023 show positive correlation($R^2 = 0.2548$ and $R^2 = 0.1288$), thus determining LST. In 2018, this slope was 23.85x with an intercept of 24.428, and in 2023, the slope was 17.917x with an intercept of 26.997, indicating a lesser influence than in previously studied years, perhaps due to seasonal influences, as these data are based on November and January.

Fig. 13. Correlation analysis between LST with NDVI and NDBI for 2002, 2008, 2013, 2018, and 2023.

The positive correlation between NDBI and LST indicates that urban heat islands and surface temperature surges are primarily caused by built-up areas. To reduce surface temperatures, it is crucial to maintain healthy vegetative cover.

NDVI and LST are strongly correlated, so a high NDVI lowers the LST, though the correlation varies by season. 2002 shows a negative correlation with $R^2 = 0.0537$, showing a negative slope of -2.6813x and an intercept of 26.901, with

NDVI variability of 5.37%, determining LST for this year. In 2008 and 2013, there is a strong negative correlation, with negative slopes of -1.805x and -11.121x, and intercepts of 26.586 and 31.225, respectively. In both years, $R^2 = 0.0134$ and $R^2 = 0.1663$, respectively, with NDVI variability attributed to 1.34% and 16.63%. In 2018, the regression shows a positive slope of 0.8804x and an intercept of 23.737, with $R^2 = 0.0013$, suggesting that LST increases with NDVI. This pattern may reflect environmental factors such as high altitude or the presence of water, which can produce a positive correlation. In 2023, the regression shows a slope of -3.4508x and an intercept of 26.77, with $R^2 = 0.0153$, indicating that NDVI variability explains 1.53% of the variation in LST.

Based on these findings, we conclude that although vegetation cover (measured by NDVI) may influence temperature patterns, other factors, such as urbanization, surface characteristics, and localized climatic conditions, are more important in determining LST fluctuations [10].

IV. RESULTS AND DISCUSSION

Figures 2 to 6 show LULC changes over time, indicating a significant shift in land-surface composition, with an increase in built-up areas at the expense of natural land cover and water bodies. In addition to demonstrating an ongoing process of urbanization, this trend suggests that it will likely continue in the future. In addition, the analysis of LST in Figures 8-12 revealed a significant upward trend in land surface temperatures, particularly a marked increase in mean temperatures between 2002 and 2023. The increase in temperature is closely linked to the expansion of built-up areas, thereby highlighting the UHI effect [11]. In the south and southwest regions, which are undergoing considerable urban development, predicted LST scenarios for 2032 indicate hotter zones. These predictions indicate an amplification of the UHI effect, raising concerns about the region's socioeconomic and environmental sustainability. Furthermore, the correlation analysis of the LULC indices revealed a key insight. Built-up areas have a progressively greater influence on temperature patterns, whereas vegetation cover seems to have a diminishing impact. Urbanization has intensified, reinforcing the UHI effect and causing a rise in temperature [12]. Land use (LU) assessment shows that vegetation and water features act as thermal sinks, lowering LST, whereas bare and impervious urban zones exhibit elevated LST. Positive LST correlations with NDBI and negative correlations with NDVI are evident [13].

A. Change in Developed Areas

Developed areas encompass all man-made structures, such as roads, pavements, and infrastructure. Between 2002 and 2023, these areas experienced an exponential increase in development, with a 34.52% rise.

B. Change in Waterbody

Lakes, rivers, and man-made tanks have decreased by 70% due to encroachment. By comparison, man-made structures such as roads and infrastructure have increased exponentially by 34.52% in developed areas from 2002 to 2023. .

C. Vegetation Cover Changes

This growth indicates a positive trend toward sustainable land use and environmental conservation. As more areas are cultivated and managed for forestry, the region benefits from enhanced biodiversity and improved air quality. Additionally, increased vegetation can help mitigate the effects of urbanization by providing wildlife habitats and reducing urban heat islands.

D. Changes in Agriculture

The amount of agricultural land has declined by 23.15 percent over the past few years. This decline is primarily because most of these lands are now being developed or used for infrastructure projects.

V. CONCLUSION

The urban expansion pattern of the Bengaluru Metropolitan Region is shown in Figures 2-6. The expansion of urban areas is evident in all directions, though it is primarily concentrated in the south and southwest. Expanding initially at its periphery, then progressively moving southward, it first appeared in the southern part of the country. In-migration from rural areas, motivated by better living standards, better career opportunities, and other factors, contributes to urban growth. In addition to being one of India's major cities, Bengaluru has experienced significant urban growth, largely driven by industrialization, making it home to numerous foreign immigrants and the headquarters of many Information Technology (IT) companies. Using remote sensing and geographic information systems, this study maps urban sprawl and land-use changes and analyzes them in detail over time. Satellite data have been found to be useful for mapping and measuring the size of urban areas over various time periods. Because land is scarcer and more expensive in core areas, this study shows that land use and cover are changing more quickly, especially in the periphery. In Bengaluru, rainfall patterns, average temperature, and the ecosystem are adversely affected by reduced vegetation. This study highlights a clear thermal contrast between built-up areas and green spaces. The relationship between Normalized Difference Built-Up Index (NDBI) and Land Surface Temperature (LST) remained consistently positive across all years, indicating that urban expansion is the primary driver of the Urban Heat Island (UHI) effect. Conversely, the relationship between Normalized Difference Vegetation Index (NDVI) and LST is predominantly negative, demonstrating that vegetation serves as a critical cooling mechanism, as shown in Figure 13. Correlation analyses of LST, NDVI, and NDBI have been conducted for 2002, 2008, 2013, 2018, and 2023. The cooling influence of green cover was most significant in 2013, accounting for 16.63% of temperature mitigation, while other years, such as 2002 (5.37%), 2008 (1.34%), and 2023 (1.53%), also showed a negative correlation. A minor anomaly in 2018 (0.13%) likely stemmed from external factors such as altitude or water bodies. Depletion of local water resources is indicated by a decrease in water bodies. From 2002 to 2023, the Land Use/Land Cover (LULC) shows a 9.87% decrease in waterbodies. This is mainly due to encroachment and the drying up of Bengaluru lakes for commercial purposes.

There is a growing trend of LULC change occurring at an accelerating rate, most notably in the peripheries of cities. Based on the findings of this study, green spaces play a significant role in shaping LST variations in urban areas. Moreover, in the future, with the help of both public and local governing bodies, focus should be on initiatives that increase green cover in urban areas through green standards such as urban forestry, pocket parks, green roofs, and vertical gardens, as well as on implementing sustainable water management techniques. The rising LST trends can be further slowed by creating more open spaces with greater green cover and by conserving or expanding urban water bodies. The development of urban infrastructure should be governed by these standards. To obtain a more detailed understanding of UHI formation, further studies should examine neighborhood open green spaces alongside multiple day and evening readings and seasonal variations to enable more in-depth analysis.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work

ACKNOWLEDGMENT

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DATA AVAILABILITY

Landsat and IRS satellite imagery were used for this study. IRS data were retrieved from Bhuvan Open Access Hub, and Landsat imagery was downloaded from Google Earth Explorer.

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