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Research Paper

A Decadal assessment of Land Surface Temperature Vegetation Index Built-up Index and Land Cover

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ABSTRACT: *Land use/land cover change analysis is one of the key strategies for managing and tracking natural resources and monitoring as well as mapping the shift. The changes result in an increase in land surface temperature of the city areas due to urbanization. The study area selected for the present study is Delhi, the National capital of India. The study compares land use and land cover changes from 2014 (Landsat 8) to 2023 (Landsat 9). A totalof five classes were selected for the analysis: vegetation, built-up, scrubland, waterbody, and agriculture for both datasets. A good degree of agreement was found in the classified maps, the overall accuracy attained was 86% (kappa 0.82) for 2014 and 90% (kappa 0.87) for 2023. The change detection suggested that there is an increase in land cover for built-up (+3.80) and also in the natural vegetation (+5.49) and a decline was observed in scrubland (-1.51) and agricultural areas (-7.91). Furthermore, the correlation was also studied with the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI). The reported results depicted that there exists a negative correlation of Land surface temperaturewith NDVI for both the time period and maximum in 2014 (R^2=0.4426) and a positive one was found with NDBI(R^2=0.6804). The study could be helpful in a way to collaborate data on urban growth, and land use change with mapping of current changes. Land cover change studies are useful for local government and urban planners to create future plans for the city's sustainable development.*
KEYWORDS:*LULC, Delhi, Landsat, Correlation, LST, NDVI, NDBI*

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I.INTRODUCTION

Urbanization has contributed to the transformation of most of the landforms on the Earth's surface to experience abrupt changes. The changes result in untoward outcomes from which Land Surface Temperature (LST) is prominent. It tends to hinder the natural flow of energy exchange by exerting pressure on the natural environment [1]. Studies related to LU/LC change are highly important, they not only provide the direction of changes but also towards its monitoring. The accelerating degree of urbanization is one of the main contributors to the changing land dynamics. The transformation of the rural area into an urban region due to economic growth and development, as well as individuals moving from rural to urban habitats, is what allows the urban-to-rural ratio to change.LU/LC studies have emerged as essential tools for managing natural resources and comprehending the varied effects that human activity has on the environment. It is reported that between 1900 and 1999, the number of people living in cities increased by more than 10 folds, from 224 million to 2.9 billion. According to statistics from the United Nations, the percentage of people living in urban areas surpassed 50% in 2006 and will approach 60% in 2020. While it is anticipated that there would be a nearly 2 billion rises in urban populations over the next 30 years, there will actually be a little reduction in rural populations, from 3.3 billion in 2003 to 3.2 billion in 2030 [2]. Population growth in the national capital has also been exponential. Delhi, one of the world's fastest-growing cities, has seen a remarkable increase in population from a meager 405,800 in 1901 to 16,753,200 in 2011 [3]. Similarly, it is mentioned that Delhi's population density went from 6352 people per square kilometer in 1991 to 11,297 people per square kilometer in 2011 [4]. The primary reasons for the current trend of urbanization in emerging economies include rural-urban migration, the regional growth of urban zones through colonial expansion, and the transition and reorganization of rural regions into micro-urban towns [5]. The exclusive cultural model is yet another aspect that draws individuals to the metropolitan area. According to the report by Delhi Human Development (2006), 2.22 million immigrants visited Delhi between 1991 and 2001, a significant increase over the 1.64 million who did so between 1981 and 1991 [6]. Both the influx of new immigrants and the suburbanization of the working class outside of the central city are the main drivers of the growth of the metropolitan periphery. The city is vulnerable to rapid urban growth as a result of the Indian government's acceptance of 100% FDI in real estate and infrastructure [4]. Reductions in agriculturaland related activities, as a result, have decreased the primary sector's contribution to Delhi's economy. For the intent of deciding, planning, and implementing land use plans to satisfy the growing demand for basic human necessities and welfare, knowledge of land use and land cover, as well as options for their best use, is vital. The dynamics of land use as a result of changing needs brought on by population growth are also tracked with the use of remote sensing technologies. Traditional methods for detecting changes in land cover are based on comparing successive remote sensing-derived land-cover maps, but ground surveys are often the conventional method of monitoring land use and urban growth. Ground surveys cannot be conducted in quick succession due to organizational issues and time constraints, hence they are unable to produce the necessary time series data. While this is going on, using data from remote sensing, the problem is readily fixed. As a result, the use of methods like image processing, remote sensing, and aerial photography becomes crucial.LU/LC change andLST are in a cause-and-effect kind of relationship. The effects are documented in the literature, the changes directly or indirectly alter surface heat fluxes.Studies have reported the fact corresponds to Urban Heat Island (UHI) effect which was supposed to be a local phenomenon but reported throughout the world in the city areas due to the changing land cover type [7,8,9].In order to analyze land surface temperature, spatiotemporal trend analysis of urban impervious surfaces in urban clustersare crucial. Over the past several decades, urban growth and dynamics related to LST have been documented in countless locations throughout the world using remote sensing and image processing. Remote sensing by using a spectral dataset integrates the field data in a GIS server to derive extended knowledge by using mathematical modeling and analysis. The analysis was done by using several parameters out of which indices are among the important ones. There are various indices that are related to mapping the features, here in the study two of them were used and discussed. For the analysis of vegetation cover, the Normalized Difference Vegetation Index (NDVI) is preferred, and for built-up Normalized Difference Built-up Index was used. The objectives of the study are to analyze LULC changes in the Delhi region from 2014 to 2023 by utilizing Landsat 8 and 9 data, in addition, to evaluating change detection for the same, the results were correlated with the indices (NDVI, NDBI) values and LST was also assessed in terms of spatiotemporal variation.

II.METHODOLOGY

Initially, the collection of Toposheets from the Survey of India for preparing the study area boundary shapefile was done. The satellite images required for the study were downloaded from the USGS (United State Geological Survey) Earth Explorer. Further processing of the image and interpretation part was carried out in ERDAS Imagine software. The obtained data set (supervised images of both years) were analyzed for each and every individual class and the composite maps were prepared in ArcGIS software. The methodology followed is further explained in the flowchart mentioned (Fig. 2).

2.1 Study area: Delhi, the national capital territory of India lies in the region between $28^0 24'17''$-$28^0 53'00''$ N and $76^0 50'24''$-$77^0 20'37''$ E with a total area of 1483 km^2. The area is divided into eleven districts namely: New Delhi, Central Delhi, West Delhi, North Delhi, North West Delhi, South Delhi, South West Delhi, South East Delhi, East Delhi, North East Delhi, and Shahdara. Some of the adjacent satellite cities, like Gurgaon, Noida, Faridabad, and Ghaziabad, were also flourishing eventually surrounding Delhi. The study area is located between the Himalayas in the north, the Aravalli mountains in the south, and the Yamuna River in the east from a wider geographical context. The mean sea level is between 213 and 290 meters above sea level. Due to the geographical extent mentioned the weather conditions are dry cold winters (1-3^0C) and extreme peak temperatures (45-47^0C) in summers. The average rainfall was reported to be around 790mm and monsoons are the prime climatic factor on which most of the agriculture depends (Fig. 1).

2.2 Satellite data used:The data was acquired from USGS earth explorer. The images were selected on the basis of the minimum cloud cover possible. The images downloaded were of the same season for the years for better comparison. Further details were mentioned in the table given below (Table 1):

Table 1: Satellite dataset (OLI-TIRS) used

Satellite	Acquisition date	Path/row	Cloud cover %
Landsat 8	09-02-2014	146/040	4.83
Landsat 9	10-02-2023	146/040	0.74

2.3 Delineating study area: The study area has been delineated using city plan maps received from Delhi Municipal Corporation and Survey of India Toposheets at a scale of 1:50000. The Landsat picture is sub-setted using the resulting base layer. This base layer is the study area shapefile which is helpful in masking the study area from the satellite imagery.

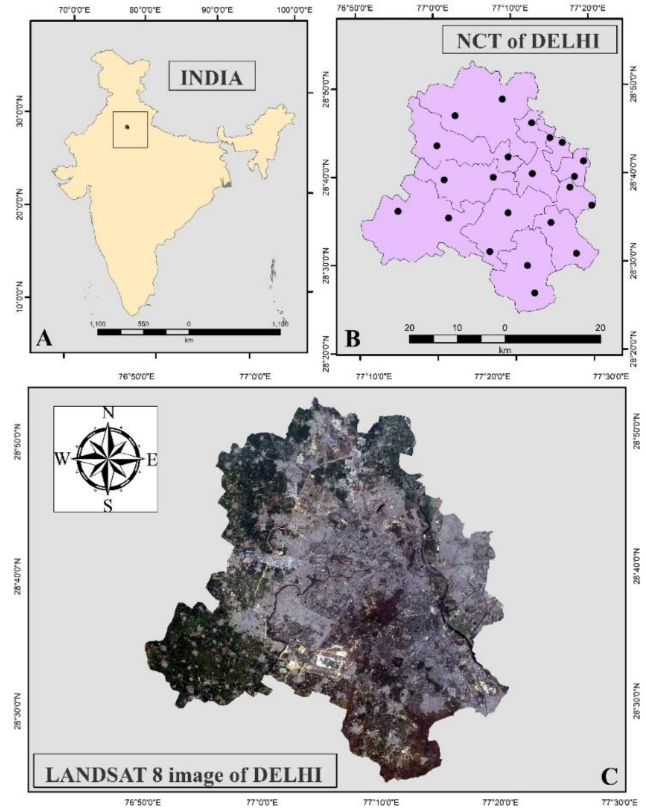

Figure 1: Study area map showing a) outer boundary of INDIA, b) sampling locations within the study area, and c) Landsat 8 true color (4,3,2) image of NCT of Delhi

2.4 Classification: To create the composite image, stacking is done on 1-7 bands.The classification is done by using the maximum-likelihood algorithm [5] used in the supervised classification technique. The FCC (false color composite, 543) image was used wherever pixel clarity was not confirmed (Fig. 3). FCC images are very helpful during the whole classification as they are not true to what we generally see, enabling the purpose of selecting the pixels. Finally, the classification provides an idea of land cover for the analysis of the study area. The classes identified for the present study were: vegetation, built-up, scrubland, waterbody, and agricultural areas.Fifty training regions (belonging to homogeneous pixels) were chosen for each category of LULC. A similar category of signatures was sorted as a new spectral signature class and the same step is repeated for the other image as well(Fig. 4).

2.5 Accuracy assessment: The LULC classification and mapping process includes the post-classification accuracy assessment, which is used to evaluate the accuracy of the classified images. The categorization accuracy measures the output quality of maps and aids in determining whether a map is appropriately classified. Studies have already employed methods like the Kappa coefficient, error matrices, and index-based methodologies for evaluating the accuracy of created LULC maps [5,10,11]. Using 500 randomly chosen points (100 for each class) through stratified random sampling, the Kappa coefficient technique is employed in this study to assess the precision of the maps generated. The points were chosen to represent all areas of the research region and equally represent each LULC class. The reference data used were the Google Earth Pro domain along with ground truthing. The estimated overall accuracy was observed to be 86% and 90% for 2014 and 2023 while kappa statistics were reported to be 0.825 and 0.875 respectively (Table 2).

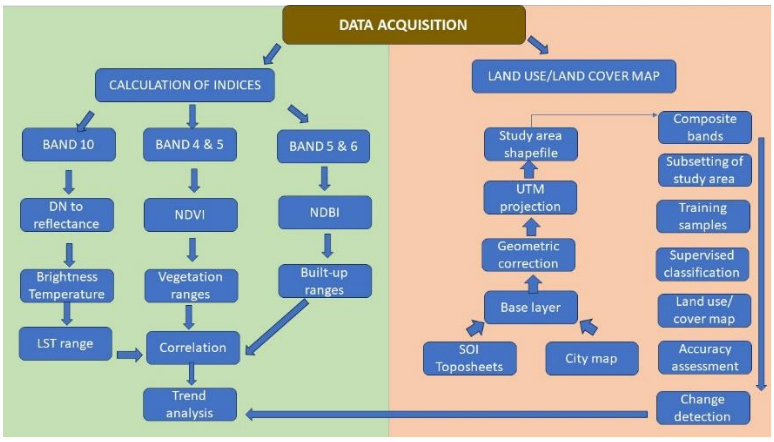

Figure 2: Flowchart of the methodology

2.6 Change detection analysis: Change detection analyses identify and quantify differences in satellite datasets taken at different times at a specific location. This approach is highly useful in identifying various changes occurring in land use classes, such as increases or decreases in any set of classes that can be measured simultaneously [15,16]. The final results can be shown in the form of separate maps (also known as composite maps) for each class. These types of studies are highly useful when an area is observed for a specific timeline.(Fig. 5).

2.7 Deriving Indices from Landsat Data

2.7.1 NDVI: The Normalized difference vegetation (Fig. 6) utilizes the RED band and NIR (near infrared) bands of the Landsat data which provides the absorption and reflectance range for plants. It can be computed from the following band equation:

$$NDVI = NIR - RED/NIR + RED$$

2.7.2 NDBI: Normalized difference built-up index (Fig. 7)is computed from the range of shortwave infrared and near-infrared:

$$NDBI = SWIR - NIR/SWIR + NIR$$

2.7.3 Land Surface Temperature (LST): For computing Land Surface Temperature several steps were followed which are summarized in the flowchart (Fig. 8) and it is derived by using the Landsat 8 user handbook [14].

2.7.4 Correlation: It is determined by plotting the values of LST against the NDVI (Fig. 9) and NDBI (Fig. 10). It gives a measure of significant relationships among parameters. Its values range from -1 to 1. The values close to 1 are highly correlated and determine a positive relationship. It is denoted by R^2.

III. RESULTS AND DISCUSSION

The analysis was primarily based on the difference in land use cover over time (2014-2023). These types of short-term (in terms of land use change studies) studies are helpful in understanding the pattern and local changes and mitigating them right away. The LU/LC (Fig. 4) mapsinclude a total of 5 classes: vegetation, built-up, scrubland, waterbody, and agriculture. In a short span of time, the study area has shown significant changes in terms of land cover change in each class (Table 4). Various studies have documented changes in land use over a considerableamount of time [5,11].The north-eastern, west, and central region of the study area hasreached saturation in terms of build-up cover. Some of the northern parts, Rohini and Dwarka were still in the developing phase and are nevertheless exhibiting evidence of continued expansion. The changes in the land use classes were provided in Table 3.The changes are clearly visible as encroachment of the built-up area (Fig. 4) in the agricultural areas of the northern and southwestern regions of the study area can be observed. Less vegetation cover is observed in the central ridge (Fig. 5), although overall the green cover can be observed to improve credited to Delhi government for implementing various practices to improve [12,13] the green cover (Fig. 10). Overall, scrub lands have also reduced to a certain extent. All this can be statistically validated through the corresponding data analyzedby comparing the two imagesand finally given as percent change (Table 3).

Table 2: Accuracy assessment of the land use classes

Land use classes	Accuracy for 2014		Accuracy for 2023	
	Producer's	User's	Producer's	User's
Vegetation	0.80	0.85	0.95	1
Built-up	0.78	0.9	0.9	0.85
Scrub land	0.82	0.7	0.95	0.76
Waterbody	1	0.95	0.75	1
Agriculture	0.9	0.9	0.95	0.95
Overall accuracy	0.86		0.90	
Kappa	0.825		0.875	

3.1 Accuracy assessment: This is a method to validate the classified supervised pixels in order to access the precision within the classification technique used. The process finally generated an error matrix table which includes the number of correctly classified pixels and vice versa. The number of accurately classified points determines the accuracy of the image. The result of the accuracy assessment is given in Table 2. The overall accuracy achieved by classification was 0.86 for 2014 and 0.90 for 2023. Agood degree of agreement was achieved for both of the years summarize to more than 80 percent.

3.2 Change detection (visualization approach): The maps were prepared in ArcGIS software. These maps are the result of a combination of the two different LULC maps that were mentioned earlier (Fig. 4). Composite maps are helpful for better understanding as they contain only a single class from which the changes can be easily depicted. The composite maps are the result of an overlay of different themes on a base map. These types of maps are very helpful for temporal studies as we can show the slightest variation efficiently. The detailed changes were further discussed with the change detection analysis.

3.3 Change detection (statistical approach): The data from the five LULC classes of the study area served as the basis for the analysis of the land cover transformation that was provided in this research. The maximum relative changes were observed in agriculture (-7.9%) and scrubland (-1.5%) in terms of land cover area. Vegetation and built-up were the most positive changes (Table 3). The change detection was evident with the To-and-From algorithm (Table 4).The "To and From" approach can be used to identify the change in areas within remote sensing data from two separate time periods by determining the shortest path between each pair of pixel pairs. The approach can be used to determine how the spectral characteristics of the same pixel location in two separate images differ from one another. The method involves creating a distance matrix that contains the spectral value differences between every pair of pixels in the two images.

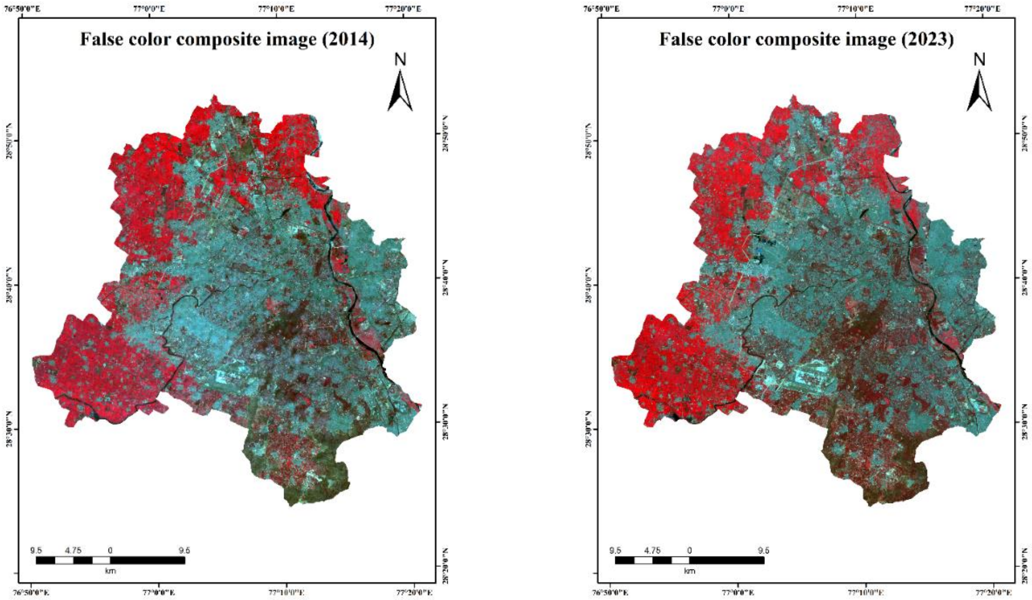

Figure3: False color composite image for the years 2014 and 2023

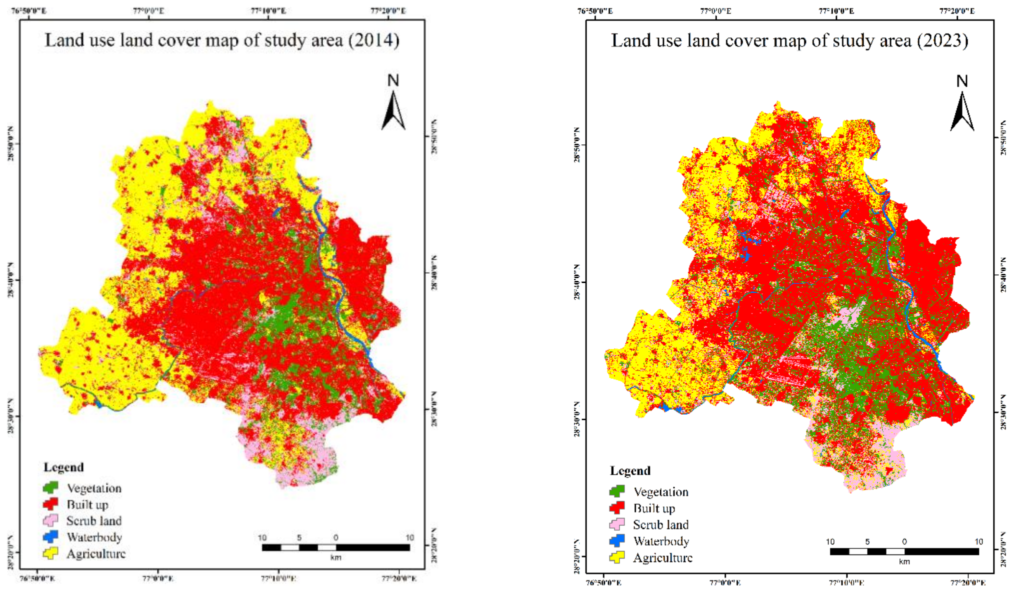

Figure4: Land use land cover map of the study area for the years 2014 and 2023

Table 3: Relative change percent of each land use class

Land use classes	Area_2014	Area in %	Area_2023	Area in %	Relative change %
Vegetation	162.502	10.940	244.158	16.438	5.497
Built-up	686.309	46.205	742.852	50.012	3.807
Scrub land	167.514	11.278	145.091	9.768	-1.510
Waterbody	19.736	1.329	21.513	1.448	0.120
Agriculture	449.287	30.248	331.747	22.334	-7.914

The matrix is initially filled with the spectral value difference between the relevant pixels in the two images. The algorithm then determines whether there is a shorter path between each pair of pixels by taking into account intermediate pixels. The distance matrix is updated if a shorter path is discovered. The areas with significant changes between the two time periods can be found using the distance matrix generated. The distance matrix's high-valued pixels represent regions where there have been large changes in spectral values. The "To and From" approach can effectively determine the difference in spectral values between all pairs of pixels in two images, making it helpful for change detection in remote sensing applications.

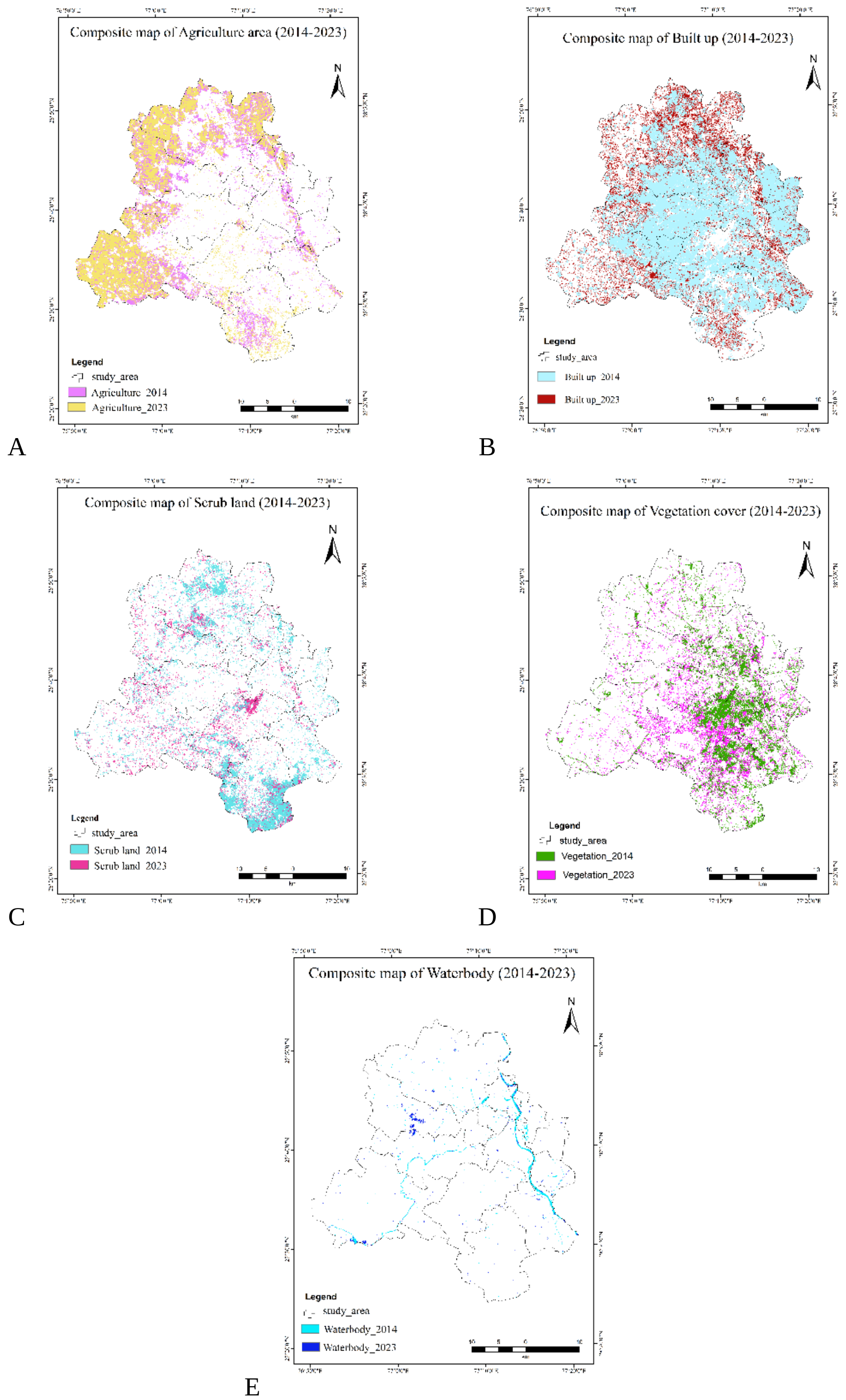

Figure 5: Composite maps of each land use class a) agriculture, b) built-up, c) scrubland, d) vegetation, and e) waterbody.

Table 4: Change detection matrix for LULC (2014-2023)

Year	2023					
2014	Vegetation	Built-up	Scrub land	Waterbody	Agriculture	Total
Vegetation	106.129	96.477	17.563	2.42	21.513	244.102
Built-up	33.54	529.171	60.724	3.479	115.736	742.65
Scrub land	17.027	34.228	59.94	0.289	33.518	142.002
Waterbody	1.965	3.067	1.1	12.821	2.543	21.496
Agriculture	3.798	23.254	28.111	0.703	275.74	331.606
Total	162.459	686.197	167.438	19.712	449.05	1483.86

3.4 NDVI: NDVI, which stands for Normalized Difference Vegetation Index (Fig. 6), is an important index used in remote sensing and vegetation-related studies. It provides information about the density and health of vegetation in a given area. The resulting NDVI value ranges from -1 to +1, with higher values indicating a greater density and healthier vegetation. The ranges can be given as Values close to -1: non-vegetated or barren areas, such as water bodies, rocks, or barren land. Values close to 0: sparse vegetation or very little green cover. Values between 0 and 1: areas with moderate to dense vegetation. The higher the value, the denser and healthier the vegetation. The computed map range of NDVI for 2014 and 2023 were -0.132 to 0.525 and -0.073 to 0.512. From Table 5 the changes can be observed as there is an upsurge in the area corresponding to low (from 378.57 to 409.56 sq. km), moderate (from 234.49 to 323.23 sq. km), and high (from 176.15 to 193.73 sq. km) classes which are supported by the fact that Delhi Government is implementing several schemes and missions to improve the vegetation cover and the positive values are in line with the earlier studies [12,13]. It can also be seen as a slight decrease in scrubland area (Table 3).

3.5 NDBI:NDBI, or Normalized Difference Built-Up Index, is another index commonly used to identify built-up or urban areas. It provides a quantitative measure of the presence and intensity of built-up structures. The resulting NDBI value typically ranges from -1 to +1, with higher values indicating dense built-up or urban areas. The values correspond to an insight to land cover: Values close to -1: non-built-up or natural areas such as vegetation, water bodies, or bare land. Values close to 0: mix of built-up and non-built-up areas. Values close to +1: These values typically indicate dense urban areas with a high concentration of built structures.

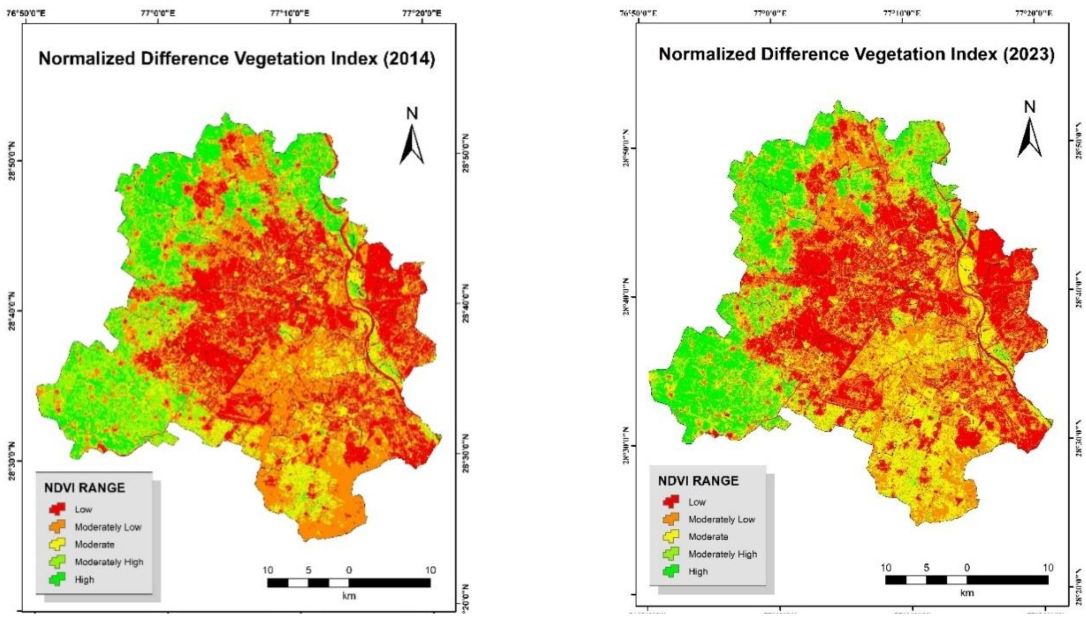

Figure 6: Normalized Difference Vegetation Index for the years 2014 and 2023

The range of NDBI (Fig. 7) was observed to be -0.405 to 0.324 (2014) and -.412 to 0.229 (2023). In terms of built-up cover an increase in the moderate and high (Table 5) classes is observed but as it is already clustered area new buildup structures are less observed despite this the conglomeration of the dense build-up is seen as high-rise buildings [2] which are very prominent. A decrease in the agricultural area was also observed due to the same fact that urbanization results in the loss of natural land cover. The changes in build-up and vegetation within land use/land cover are highlighted in various studies and it is not a local phenomenon.

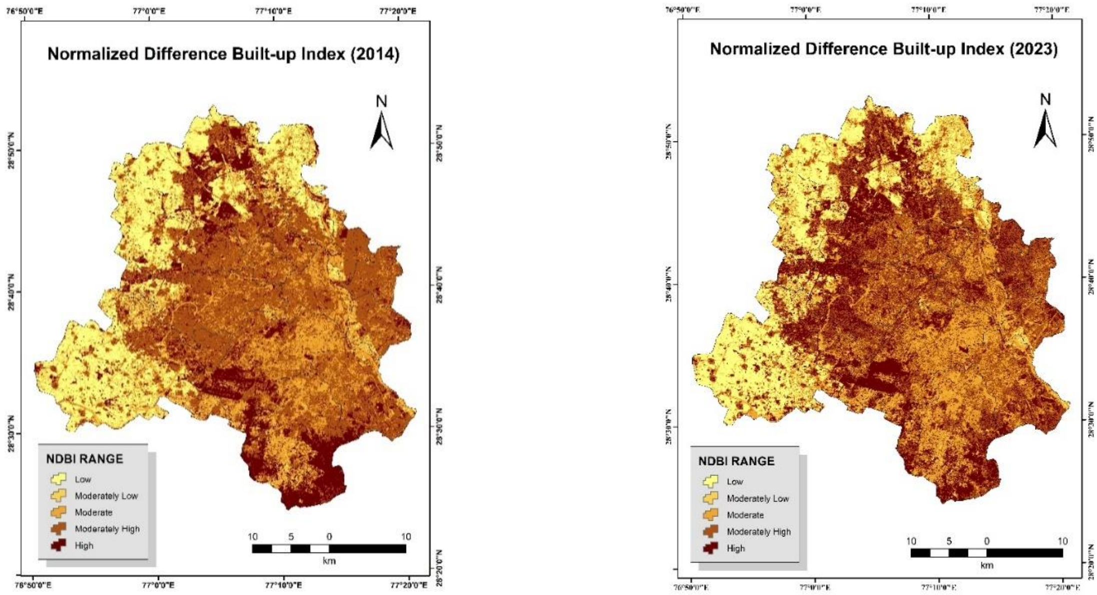

Figure 7: Normalized Difference Built-up Index for the years 2014 and 2023

3.6 LST: Land Surface Temperature refers to the temperature of the Earth's surface. It represents the thermal energy emitted (8-14 micrometers) by the land surface, including the top layer of soil, vegetation, and built-up structures. LST [7] is an essential parameter in various fields, including climate studies, urban planning, agriculture, and environmental monitoring.Several factors influence land surface temperature, including solar radiation, atmospheric conditions, land cover, and surface properties. It can be used for studies related to Diurnal Variation,Surface Characteristics,Urban Heat Island Effect,Climate Studies,Urban Planning,Agriculture, Natural Resource Management, and so on.

As the LST [7,8,9] is concerned it is evident that the loss of vegetation and increase of buildup would result in an increase in the temperature range. From the analysis, it was observed that the lowest value corresponds to vegetation, and the highest value which predicts the scrub land tends to show lower temperature ranges because of an increase in vegetation cover throughout the study area. The practice of increasing the green cover is human-induced and intentional but it is providing good results by lowering the temperatures to some extent. Out of the LST ranges all the moderate values which correspond to the buildup show a rise in temperature graph (Fig. 8). As the study emphasized an increase in built-up structures the LST values were also reported to be on the higher side as compared to 2014. The range was 11.3 to 22.9 (2014) which has increased to 14.86 to 30.03 (2023).

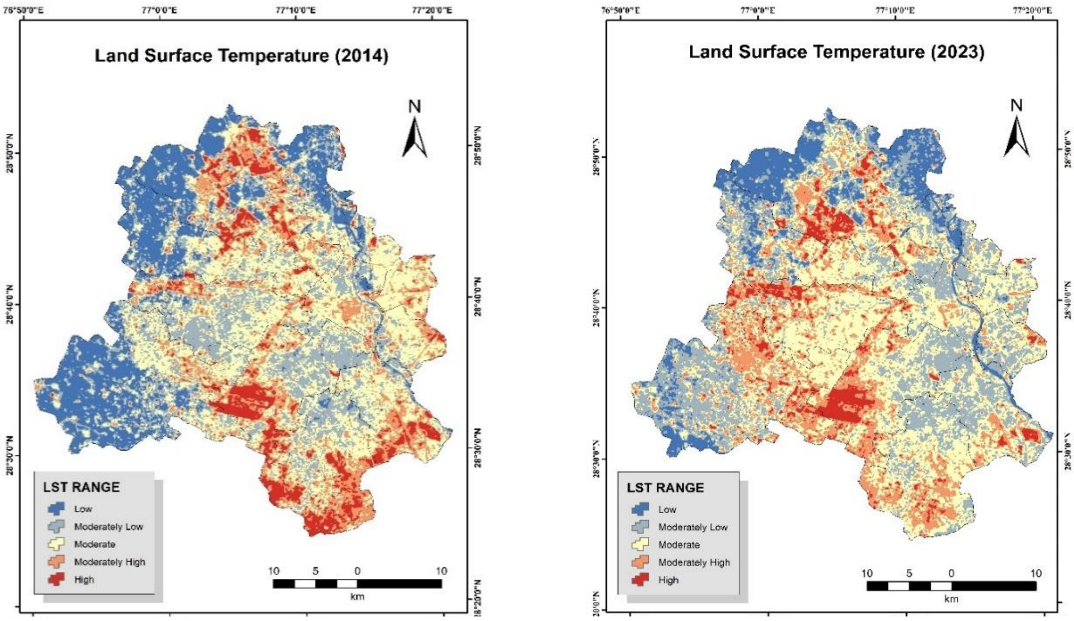

Figure 8: Land Surface Temperature for the years 2014 and 2023

Table 5: Value range of each class for index

Class	NDVI_2014	NDVI_2023	NDBI_2014	NDBI_2023	LST_2014	LST_2023
L	-0.132 to 0.066	-0.073 to 0.089	-0.405 to -0.233	-0.412 to -0.243	11.3 to 13.7	14.86 to 19.50
ML	0.066 to 0.135	0.089 to 0.158	-0.233 to -0.133	-0.243 to -0.145	13.7 to 15	19.50 to 20.93
M	0.135 to 0.228	0.158 to 0.241	-0.133 to -0.047	-0.145 to -0.067	15.1 to 16.1	20.93 to 22
MH	0.228 to 0.334	0.241 to 0.337	-0.047 to 0.012	-0.067 to -0.014	16.2 to 17.5	22 to 23.43
H	0.334 to 0.525	0.337 to 0.512	0.012 to 0.324	-0.014 to 0.229	17.6 to 22.9	23.43 to 30.03

Here, L= Low ML= Moderately low M= Moderate MH= Moderately high H= High

Table 6: change detection within each class from 2014 to 2023 (Area in sq. km)

Class	NDVI_2014	NDVI_2023	NDBI_2014	NDBI_2023	LST_2014	LST_2023
Low	378.5724	**409.5666**	228.1023	119.8828	265.2363	146.0475
Moderately low	506.5938	422.7498	131.1354	112.8771	353.1582	**408.0366**
Moderate	234.4959	**323.2386**	285.1461	**315.2304**	494.8893	**548.4564**
Moderately high	189.6795	136.2042	606.8808	505.0971	260.613	**300.9321**
High	176.1516	**193.7385**	234.234	**352.4121**	111.456	82.0251

3.7 Correlation

Correlation refers to a statistical measure that describes the relationship or association between two or more variables. It quantifies the extent to which the variables change together or vary in relation to each other. Correlation is often used to determine if there is a statistical relationship between two variables and to what degree they are related. The correlation coefficient indicates both the strength and direction of the relationship between variables. A positive correlation coefficient (ranging from 0 to 1) suggests that the variables are positively related, meaning that as one variable increases, the other tends to increase as well. Conversely, a negative correlation coefficient (ranging from -1 to 0) indicates an inverse or negative relationship, where as one variable increases, the other tends to decrease.

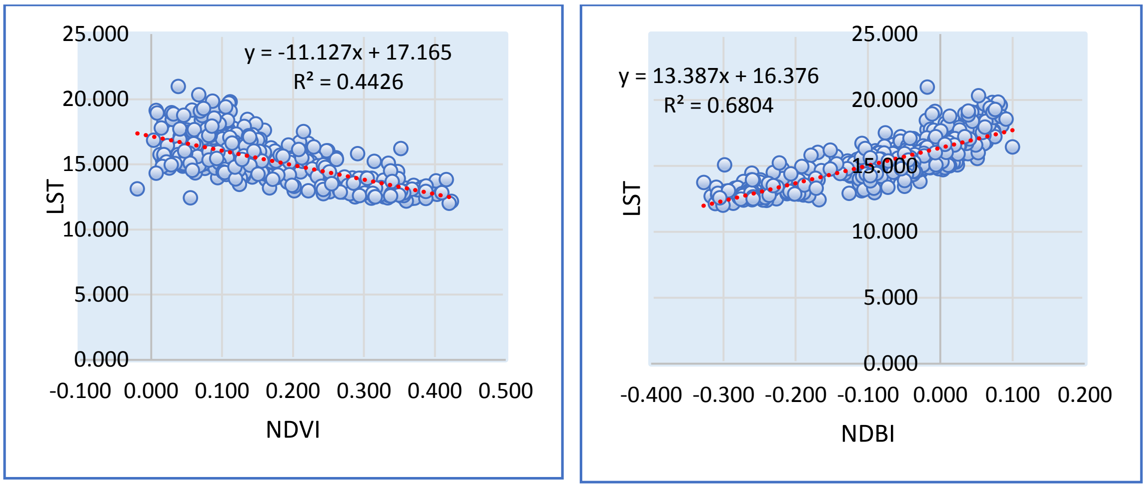

Figure 9: Correlation analysis of LST with NDVI and NDBI (2014)

3.7.1 CORRELATION LST WITH NDBI

As the correlation was observed to be on a good positive scale (R^2= 0.68, Fig. 9) and (R^2=0.40, Fig.10), it suggests a strong relationship between built-up areas and the thermal behavior of the land surface [5]. The strong correlation indicates that areas with a higher proportion of built-up structures (reflected by high NDBI values) tend to exhibit higher land surface temperatures (reflected by high LST values). This correlation is often associated with the urban heat island effect, where urban areas experience higher temperatures compared to surrounding rural or natural areas due to increased heat absorption and reduced vegetation. The built-up structures in urban areas, such as buildings, roads, and concrete surfaces, have properties that retain heat, contributing to elevated land surface temperatures.

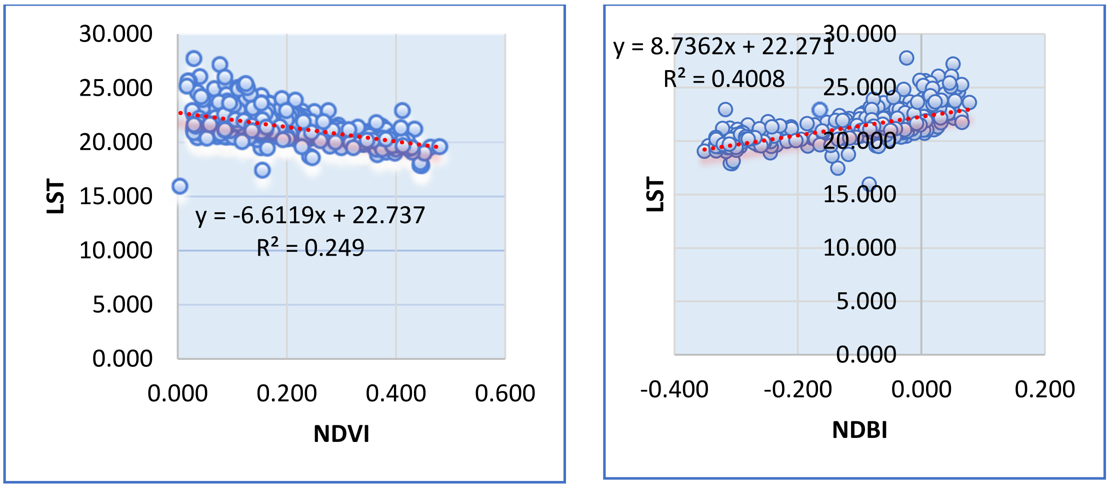

Figure 10: Correlation analysis of LST with NDVI and NDBI (2014)

3.7.2 CORRELATION OF LST WITH NDVI

The negative correlation withR^2=0.44 (2014) and R^2=0.24 (2023) indicates that areas with higher vegetation density or healthier vegetation (reflected by high NDVI values) tend to exhibit lower land surface temperatures (reflected by low LST values). Vegetation provides shading and evapotranspiration, which can contribute to the lower temperature of the land surface by reducing the absorption and retention of solar energy. Healthy and well-watered vegetation tends to have a cooling effect on the land surface. Higher NDVI values [8] indicate areas with more robust vegetation growth, often associated with adequate leaf moisture. This highlights the importance of urban green spaces in promoting a cooler and more comfortable urban environment. It can be used to identify areas with low vegetation cover or vegetation stress, which might be vulnerable to heat-related impacts or ecological disturbances.From the above results, LST has shown a positive correlation in both the time period corresponding to dense urban development and a negative correlation with vegetation indicating the possibility of intentional greening efforts, such as tree planting programs, green infrastructure, or urban forestry initiatives [12]. These efforts aim to increase vegetation cover and improve the resilience of urban ecosystems by providing shade, reducing heat, and enhancing ecological services.

IV.CONCLUSION

Monitoring of changes has a whole new dimension with the availability of satellite data from which extraction of information is possible. The present study involves the land use land cover change analysis for the years 2014 and 2023. Generally, it was observed that this type of study includes a longer time span but studies like this are also necessary to map the current shift or to take any mitigation step right at the source of generation. For the classified maps, the overall accuracy was found to be 86% and 90% for 2014 and 2023 respectively. Change detection analysis results increase in vegetation cover (+5.4%) followed by build-up (+3.8%) and a decrease in scrubland areas (-1.5%) and agricultural areas (-7.9) was observed.The waterbody has shown a slight positive variation (+0.12). The changes were also correlated by using indices with the LST. The correlation was found to be positively correlated with built-up cover and negative with vegetation. This could be summarised as an increase in built-up cover results in higher temperature and a decrease in vegetation results in the same (negative correlation). The studies related to vegetation cover result in planning informed decisions regarding vegetation management, urban greening initiatives, and heat mitigation strategies. Increasing vegetation cover, promoting sustainable landscaping, and incorporating green infrastructure can help reduce land surface temperatures and enhance thequality and resilience of ecosystems and urban environments.Overall, a high correlation between LST and NDBI indicates the thermal consequences of urban development and provides insights for implementing appropriate strategies to mitigate heat-related issues and improve the overall thermal comfort and sustainability of urban environments.

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