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Urban Morphology and Green Spaces Changes in Model Town, The Oldest Settlement of Lahore, Using Satellite Data

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Abstract
Amidst the rapid urban expansion transforming cities worldwide, this study explores three decades (1990-2021) of urban expansion in Model Town, Lahore, revealing how rapid development has affected Land Surface Temperature (LST) and green spaces in this historically unique Model town. Utilizing Landsat 5 TM and Landsat 8 OLI satellite imagery, we calculated the Normalized Difference Built-up Index (NDBI) and applied an index-based classification technique to quantify changes in built-up and non-built-up land. The results reveal a substantial increase in built-up area from 2.667 km² to 4.969 km² in Model Town, and from 455.45 km² to 807.40 km² in Lahore. Concurrently, the mean LST rose from 27.49℃ to 30.62℃ in Model Town, and from 25.72℃ to 29.17℃ in Lahore, indicating a steady increase over the study period. Additionally, vegetative cover decreased significantly, with a 13.82% reduction in Lahore and a 128.47% reduction in Model Town. These findings underscore the critical need for sustainable urban planning to manage the adverse effects of rapid urbanization on temperature and green spaces.
Keywords: Urbanization, Land Surface Temperature (LST), Normalized Difference Built-up Index, Green Space Reduction

1. Introduction

Waste is ingrained within us and is a part of all functions. It is unavoidable and increasing with our consumption patterns, economic and social development, urbanization and high density population (Pan, et al., 2019; Razzaq, et al., 2021). The developed countries produce more waste than developing countries (Liu, et al., 2018). Currently, per capita solid waste generation of developed countries is estimated around 521-759 and 109-525 kilograms for the developing countries and is increasing at the rate of 2 billion tones/year globally and will reach to 27 billion tones by 2050 (Tanmoy et al., 2012; Tawari, 2024). The waste we produce might leave our sight but stays with us for long periods of time. It is a major producer of Green House Gases (GHGs) and cannot be left unmanaged (Sharma, 2011). Cities are the main contributors of GHGs emissions in Asia (Shah et al., 2020; Asif et al., 2023).
Construction and Demolition Waste (CDW) is a major part of Municipal Solid Waste (MSW) and is close to 35% of global solid waste (Liu, et al., 2020; Asim et al., 2021). It is the residual after construction, retrofitting or demolition has taken place (Lu, et al., 2021; Elahi et al., 2021; Rehman & Ahmad, 2024). The CDW consists of concrete, bricks, glass, wood, plastic, solvents, bituminous, steel, aluminum, asbestos and soil etc. (Lam, et al., 2019; Ali et al., 2020; Roussel & Ali, 2024). Concrete is the major constituent of CDW which is inert, bulky and weighs the most and could be recycled (Pantini, et al., 2019; Yasir et al., 2021; Farhadi & Zhao, 2024).
The CDW is a global issue that consumes land and energy. The Concrete Industry, globally, burns 40% of energy and consumes 50% of raw material and produces 50% of CDW (Bhattacharyya, et al., 2014). In European Union out of 3000 Million Tons of waste produced per year, 25 to 30 percent consists of CDW (Bravo et al., 2015; Ullah & Ali, 2024). In the USA 569 million Tons of CDW was generated in year 2017 (U.S. Environmental Protection Agency, 2020). The literature states that from 2015 to 2035, due to housing sector in Asia and Africa, 1.5 billion new urban residents shall be added globally with highest rate of increase in history (Duan, et al., 2019; Rafique et al., 2020). The developing countries like China, Africa, India and Pakistan, due to high urbanization rate, are expected to have increased rate of CDW production. In lieu of future development it is imperative to find ways and technologies that would reduce the burden of landfill sites by reducing the amounts of CDW.
The present study is focused on the urbanization process in Lahore’s oldest settlement of Model Town. The main aim is to detect the change in urban and built-up areas in the model town over the past three decades from 1990 to 2020. In the present study, we have acquired the Landsat data (TM and OLI) for the years 1990, 2000, 2010, and 2021 to observe the Land use changes (built-up land) in Model Town, the settlement of Lahore, Pakistan. By considering Lahore, Pakistan, as a case study and accounting for 30 years ranging from 1990 to 2021, this research aims to investigate urban land growth and housing of the marginal housing scheme of Model Town and its impact on the Land Surface Temperature (LST) and green spaces.

2. Methodology

2.1. Study Area

Model Town Society is one of the unique housing societies in its design and is considered a posh locality of the town. It is geographically located between 31.485°N and 74.326°E in the heart of Lahore. It was built in the 1920s in the suburbs of Lahore, the capital of the Punjab state in British India, and covers an area of over 2000 acres. The model town served as a unique social experiment in addition to an investigation into urban morphology.
A tiny group of individuals from each of the major sections of the Indian population were willing to live in an ideal cooperative garden town at a time when all the major sections were considering freedom and potential independent states based on religious majorities in various locations. The elevation of Model Town is about 213.15 m (699.31 ft). The urbanization and built-up pattern in Model Town have been changed from 1920 onwards. A remarkable number of buildings and houses have been constructed in the locality of Model Town. By investigating and analyzing Model Town, it becomes easy to investigate the 'hybrid' forms that arose from the blending of foreign concepts with the effects of indigenous cultures, religions, customs, and economies, a style that became a trademark of post-colonial urban growth in the area.

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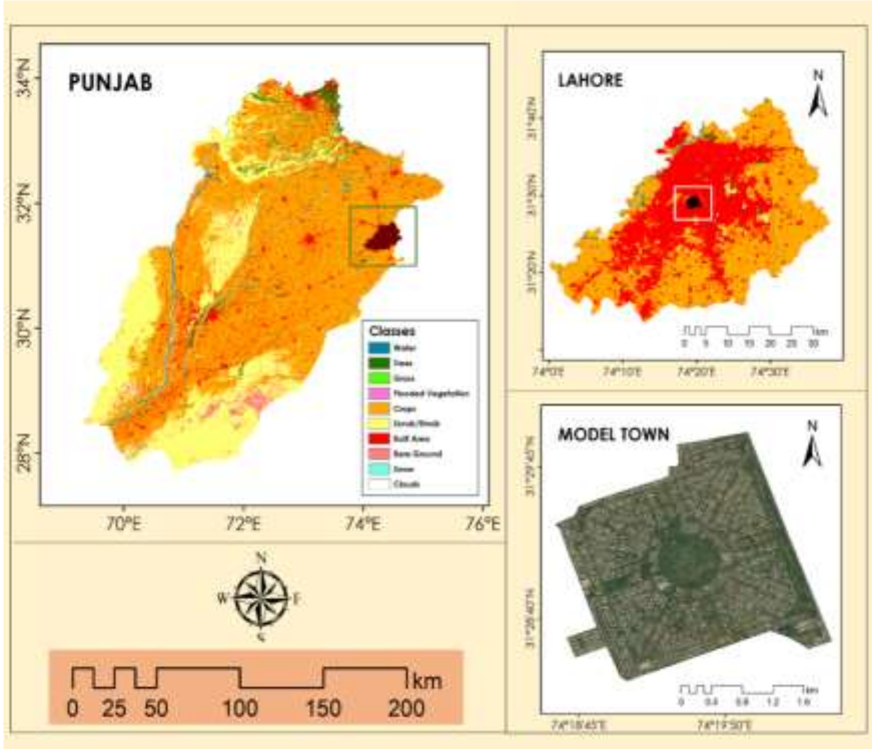

Figure 1: Study Area Map of Model Town, Lahore
Source: Author

3. Data Acquisition and Processing

3.1. Satellite Data

We have acquired four Collection 2 Level 2 Landsat satellite images for the years 1990, 2000, 2010 (Landsat 5, Thematic Mapper (TM)), and Collection 2 Level 1 Landsat satellite image for the year 2021 (Landsat 8 Operational Land Imager (OLI)). The Landsat images of Lahore with path/row of 149/38 were downloaded from the United States of Geological Survey- Center for Earth Resources Observation and Science (USGS-EROS), with less than 10% cloud cover for March and April because usually winter season fog and summer season heavy clouds due to monsoon are a big hindrance to accurately classify and assess the images. The Collection 2 Level 1/2 data of Landsat legacy acquired has improved geometric accuracy, improved digital elevation modelling, improved radiometric calibration. Therefore, no radiometric, atmospheric, or topographic correction was made. The administrative boundary for Lahore and Model Town was obtained from official sources for extracting and clipping the Area of Interest from the overall image scene.

Table 1: Satellite Images Details

Scene ID	Year	Sensor	Satellite	Resolution (m)	Date	Cloud Cover
LT05_L2SP_149038_19900316	1990	TM	Landsat 5	30	16 March 1990	1%
LT05_L2SP_149038_20000412	2000	TM	Landsat 5	30	12 April 2000	0
LT05_L2SP_149038_20100307	2010	TM	Landsat 5	30	07 March 2010	0
LC08_L1TP_149038_20210305	2021	OLI	Landsat 8	30	05 arch 2021	1%

3.2. Normalized Difference Built-up Index (NDBI)

NDBI stands for Normalized Difference Built-up Index, in comparison to the other Land Use and Land Cover (LULC) surfaces, built-up lands have higher reflectance in shortwave infrared SWIR wavelength range (1.55 – 1.75 µm) than in near-infrared NIR wavelength range (0.76 – 0.90 µm). NDBI is very useful for mapping urban built-up areas and has been computed using the equation (1) expressed as follows:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad \text{(Zha et al., 2003)}$$

Where, SWIR is middle infrared reflectance, which is band 5 of TM and band 6 of OLI. NIR is near infrared reflectance such as band 4 of TM and band 5 of OLI. NDBI values range from -1 to 1. The greater the NDBI is, the higher the proportion of built-up area is. The NDBI index was calculated by taking the two bands of each sensor as TM and OLI. NDBI was calculated by using the above expression in ArcGIS using a map algebra tool using the float function.

3.3. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is an index that is calculated from satellite data bands. It gives an approximation about the vitality and density of vegetation at a pixel based on different intensities of reflected sunlight from the visible (VIS) (0.4-0.7µm) and near infrared (NIR) (0.7-1.1µm) spectrum that is picked up by the satellite sensors. Healthy plant leaves mostly absorb light in red part of the spectrum (0.63-0.69μm) using chlorophyll to produce glucose from carbon dioxide and water in the process of photosynthesis, whereas the cell structures strongly reflect the light from the NIR spectrum (Rouse et al. 1974).

$$\text{NDVI} = \frac{NIR-RED}{NIR+RED} \qquad \text{(Rouse et al., 1974)}$$

The NIR minus red divided by the NIR plus red radiation resulted in a newly simplified image called the Normalized Difference Vegetation Index (NDVI), the difference between the NIR and red band should be larger for greater chlorophyll density.

The values of NIR range from +1 to -1, the absolute +1 NDVI value indicates reflectance captured only in NIR and no reflectance in the Red channel (which is not true), 0 NDVI value indicates that reflectance in red and NIR is the same, -1 NDVI value shows that 0 reflectance in NIR and some reflectance in Red.

3.4. Index-Based Classification Technique

Image classification techniques over a multiband satellite image can be utilized to extract information about Land Use and Land Cover (LULC) (Alam et al., 2020; Shah et al., 2021; Abid et al., 2021). There are a lot of different approaches to classifying the image, such as machine learning, object-based image classification algorithm (OBIA), supervised and unsupervised classification, and index-based classification. In this study, we have used the index-based classification technique to classify the image of Normalized Difference Built-up Index (NDBI).

The classified images for built-up and non-built-up areas over the Lahore and Model Town were obtained for the years 1990, 2000, 2010, and 2021 from Landsat 5 TM and Landsat 8 OLI using index-based classification techniques.

3.5. Area Calculation & Percentage Change Detection

The built-up area was calculated by multiplying the pixel count of built-up land by per pixel area, the area estimation of built-up land was calculated for all the four classified images over Lahore and Model Town for the years 1990, 2000, 2010, and 2021.

Built-up Area = [Built-up Pixel COUNT] * [Per Pixel Area]

Here, Per Pixel Area for Landsat TM and OLI is 30*30 m which is equal to $900m^2$ or 0.0009 km^2.

The percentage change increase was calculated by using the following expression,

$$\text{Percentage Change} = \frac{Area\ in\ Final\ year - Area\ in\ Initial\ year}{Area\ in\ Final\ year} \times 100$$

3.6. Land Surface Temperature Calculation

The land surface temperature (LST) maps for each of the years 1990, 2000, 2010, and 2021 were produced using the Landsat 5 TM and Landsat 8 OLI images.

3.7. Calculating land surface emissivity

Black body radiance is scaled by land surface emissivity (LSE), which follows Planck's law, to forecast radiation that is emitted. It assesses the efficiency of thermal energy transport from the surface to the atmosphere (Sobrino et al., 2002). To extrapolate LST from radiance data, LSE is usually utilized. Surface emissivity can be extracted from satellite data in a variety of methods (Vlassova et al., 2014; Qaiser et al., 2021). However, these methods are constrained when employed with Landsat imagery because of the single thermal band. NDVI-based methods, which rely on the percentage of vegetation (P_v) Landsat TM NDVI is an alternate (Sobrino and Raissouni 2000) as:

$$P_v = \frac{(\text{NDVI} - \text{NDVImin})^2}{(\text{NDVImax} - \text{NDVImin})^2}$$

3.8. Determining the top of atmospheric spectral radiance

The TOA spectral radiance was applied to the Landsat data, l_λ (watts / (m^2 * srad * μm) as;

$$L_\lambda = M_L\, Q_{\text{cal}} + \text{AL}$$

where Q_{cal} is the pixel DN value, and M_L represents the band-specific multiplicative rescaling factor and AL represents the band-specific additive rescaling factor. M_L and AL have values equal to 5.5375E02 and 1.18243 for Landsat-5 imagery and 3.3420E04 and 0.1 for Landsat-8, respectively.

3.9. Calculating the brightness temperature

The thermal radiations that travel in the direction of the satellite from the top of the atmosphere are measured by the brightness temperature (TB). This formula is used to calculate it:

$$T_B = \frac{\text{K2}}{\ln(\frac{\text{K1}}{L_\lambda + 1})}$$

where K1 and K2 are considered constant and their unit is watts/meter, L_λ is the TOA spectral radiance from Eq. 2. K1 and K2 represent band-specific thermal constants with values equal to 607.76 and 1260.56 for Landsat-5 imagery, and 774.8853 and 1321.0789 for Landsat-8 data, respectively.

3.10. Calculating the land surface temperature

The LST maps for the years 1990, 2000, 2010, and 2021 were derived from Landsat 5 and Landsat 8 images of the respective years as follows:

$$\text{LST} = \frac{\text{TB}}{1 + (\text{W} * \text{TB}/\sigma) * \ln(\text{LSE})}$$

where W represents the wavelength emitted radiance and σ is equal to h ∗ c/s, where h is Planck's constant, s is Boltzmann constant, and c is the velocity of light.

4. Results & Discussions

4.1. Spatial Distribution of Land Use and Land Cover

Landsat images were used to obtain NDBI and NDVI of Lahore and model town as indicated in figures 3, 6, and 11, which was further classified into two classes including built-up/non-built-up land and vegetative/non-vegetative land for Lahore and model town respectively in the figures 4, 7, 9, and 12. The spatial distribution of NDBI over the Lahore can be seen in the figure 3. It was observed that built-up land extensively increased in the study period from 1990 to 2021. It can be seen clearly that the urban sprawl has increased substantially, and a clear change can be seen spatially in the southern and central parts of Lahore (Shah et al., 2021; Asif et al., 2017). Land use and land cover change has significant impact on natural resources and services and Lahore is also impacted by them (Ahmed et al., 2021; Zafar et al., 2022; Malhi et al., 2023).

The highest built-up area has been observed in the year of 2021 with a total 807.40 km^2 and comparatively low as 455.45 km^2 in 1990 in Lahore, as shown in Table 2.

Table 2: Descriptive statistics for NDBI of Lahore

Years	Min	Max	Mean	Area of Built-up (km^2)
1990	-0.330	0.177	-0.100	455.45
2000	-0.368	0.159	-0.035	634.83
2010	-0.374	0.226	-0.119	763.97
2021	-0.426	0.293	-0.121	807.40

The same results were also mapped over the Model Town Lahore, which is in the center of Lahore. The highest built-up area was mapped in 2021 as 4.969 km^2 , and lowest as 2.667 km^2 in 1990 as shown in Table 3. The increase in the urban and building sprawl has been observed over the model town from 1990 to 2021, which can be visualized in Figure 6. Farid et al., 2022 study also finds similar results, he also investigated the rapid urbanization over the city of Lahore from 1990 to 2020 and discovered that the Built-up land had 22.9% portion in 1990, and it was increased to 33.2% in 2000, 34.2% in 2010, and 46.4% in 2020. The highest relative change from 1990 to 2020 has been found for built-up land (23.52%) at the cost of 12.82% loss in vegetation cover and 10.26% barren land. (Fahad et al., 2021; Imran & Mehmood, 2020) have also found that urbanization has shrunk the barren land and vegetation cover over Lahore. The percentage increase in the built-up land over Lahore and Model Town has been calculated to be 43.59 % and 46.32 % respectively, with the highest change in percentage increase to be found from 1990 to 2000 with an overall increase equal to 28.25 % for Lahore and 26.74% for Model Town.

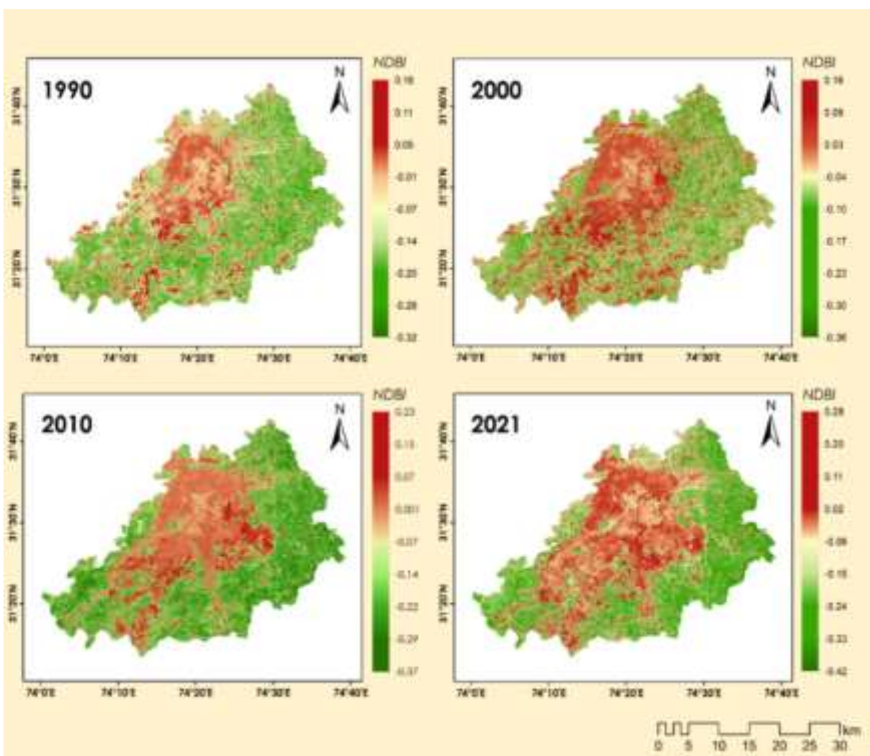

Figure 2: NDBI of Lahore for 1990, 2000, 2010 and 2021

On the other hand, the spatio-temporal distribution of NDVI over Lahore is also seen in Figure 6, and the descriptive statistics of NDVI in Table 3, it is clear from the figures and statistics that the pattern of NDVI has decreased over 30 years and the major cause for this is the increased in the distribution of urban pockets. Also, the NDVI pattern for the model town is shown in Figure 11, which shows clearly that due to the emerging housing pattern and buildings the NDVI has been showing a decreasing pattern for some time, but interestingly some plantations of more trees have resulted to show the increase in the vigor of vegetation pattern for a while. The highest vegetative cover area was observed in 1990 1045.76 km^2 and 3.98 km^2 over Lahore and model town respectively. On the other hand, the lowest vegetative area has observed in 2021 as 918.72 km^2 and 1.74 km^2 over Lahore and Model Town respectively. Around 13.82% and -128.47% of vegetative area is decreased for 30 years (1990-2021) for Lahore and model town respectively. It can also be observed from the graph as shown in the figure 8 and 13.

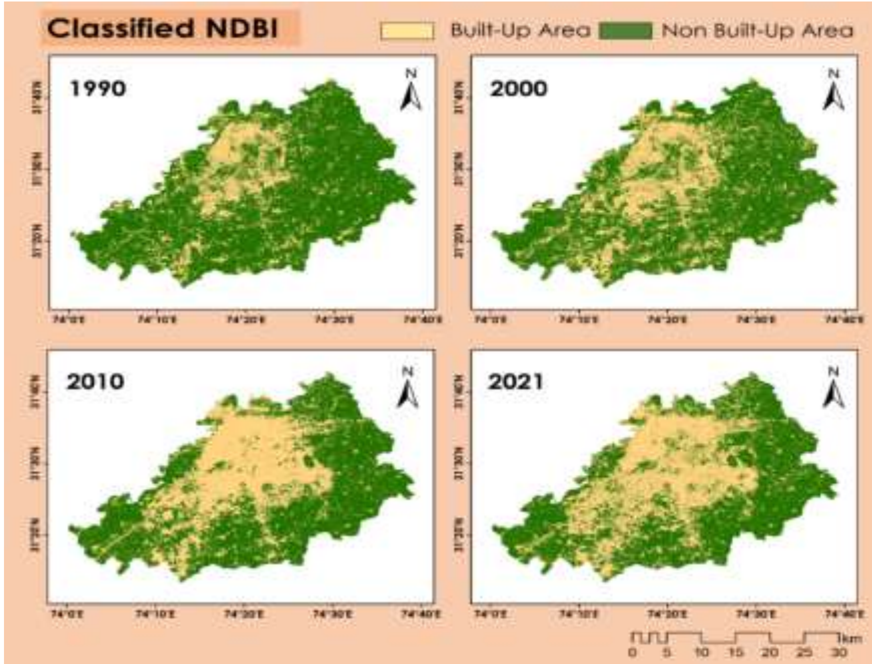

Figure 3: Classified NDBI of Lahore as built-up and non-built-up land

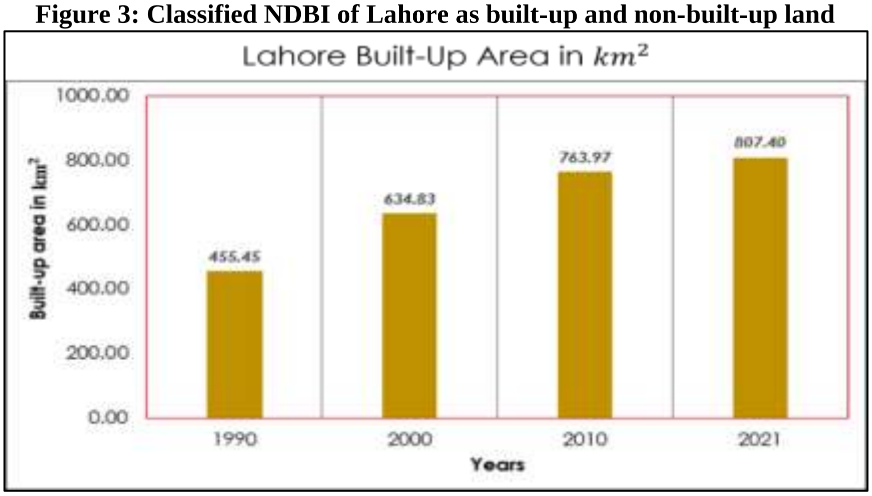

Figure 4: Built-up land of Lahore in the years 1990, 2000, 2010 and 2021

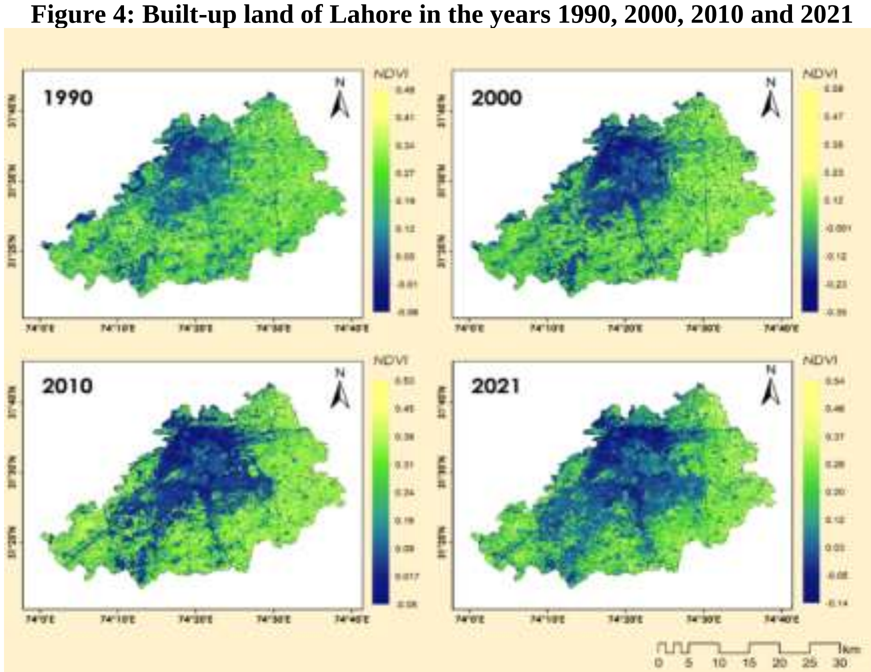

Figure 5: NDVI of Lahore for 1990, 2000, 2010 and 2021

Table 3: Descriptive statistics for NDVI of Lahore

Years	Min	Max	Mean	Std Dev.	Vegetative Area (km^2)
1990	-0.084	0.478	0.227	0.110	1045.76
2000	-0.354	0.586	0.241	0.127	1037.95
2010	-0.056	0.526	0.253	0.139	1022.76
2021	-0.141	0.546	0.227	0.137	918.72

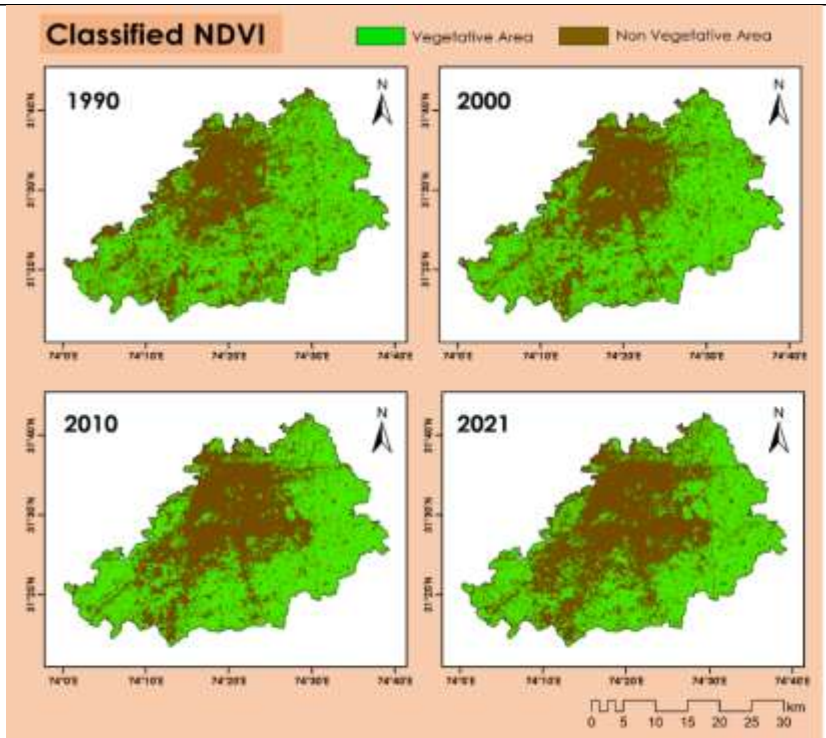

Figure 6: Classified NDVI of Lahore as vegetative and non-vegetative area

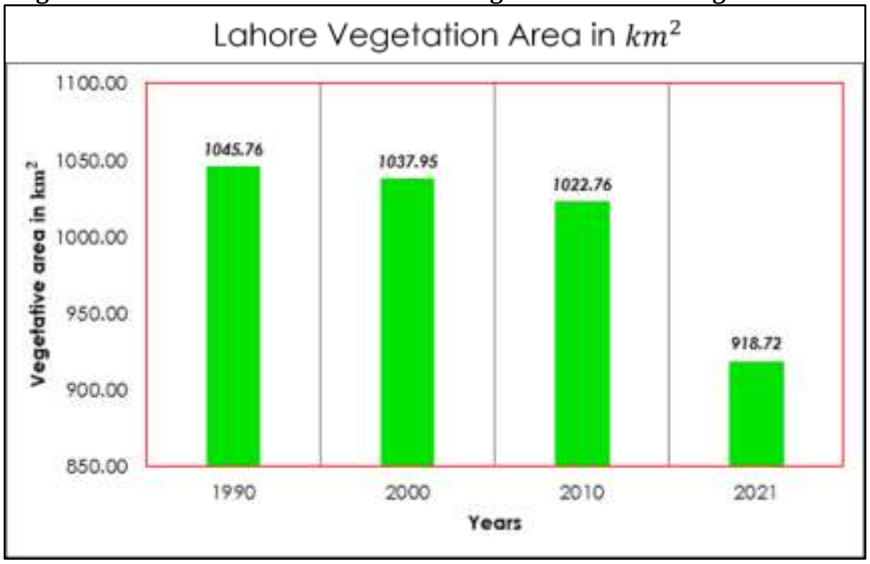

Figure 7: Vegetative Area of Lahore in the years 1990, 2000, 2010 and 2021

4.2. Spatial Distribution of LST

The Land Surface Temperature (LST) pattern of Lahore and Model Town was calculated for March 1990 to 2021. The results of LST are presented in Figure 8 and Figure 9, respectively. The results reveal that the maximum, minimum, and mean temperature have constantly increased from 1990 to 2021. Figure 8 also indicates that in 1990 the maximum surface temperature was in central and western parts of Lahore, but in 2000, 2010, and 2021, the maximum LST was spatially spread to the southern part of the city as well. The same is the case with the Model Town boundary as shown in Figure 9, the increased vehicular activity along with the rapid construction of buildings in the society have caused the mean LST to increase from 1990 to 2021. However, the minimum LST has been observed inside the central part of Model Town along with some other pockets due to the presence of parks and other recreational green areas.

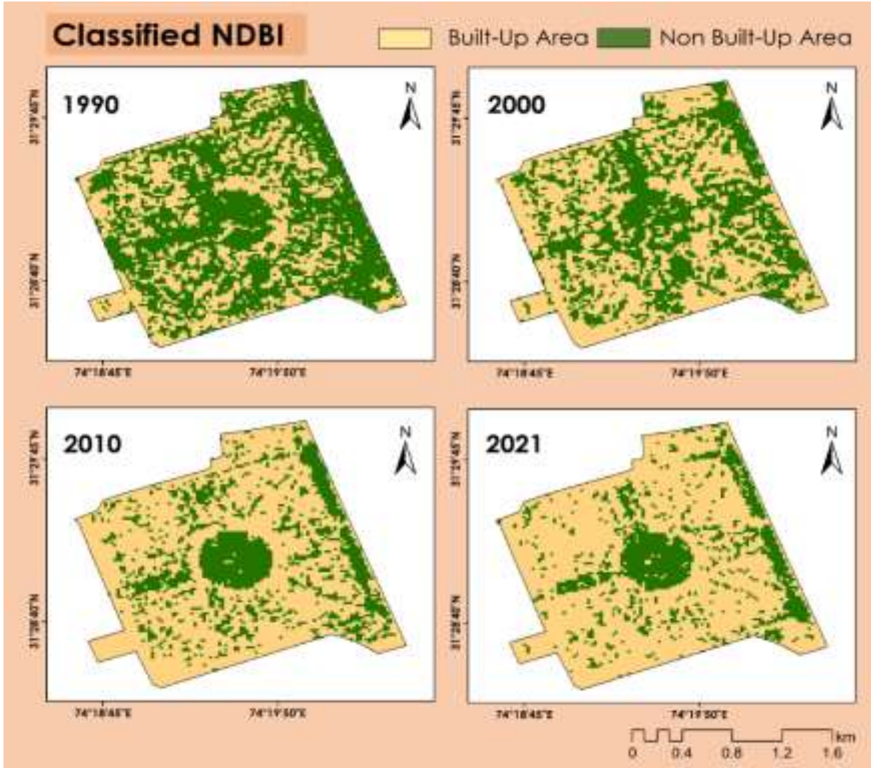

Figure 8: Classified NDBI of Model Town as built-up and non-built-up land

Table 4: Descriptive statistics for NDBI of Model Town

Years	Min	Max	Mean	Area of Built-up (km^2)
1990	-0.186	0.079	-0.020	2.6676
2000	-0.157	0.078	-0.008	3.6414
2010	-0.195	0.093	-0.023	4.6269
2021	-0.196	0.105	-0.043	4.9698

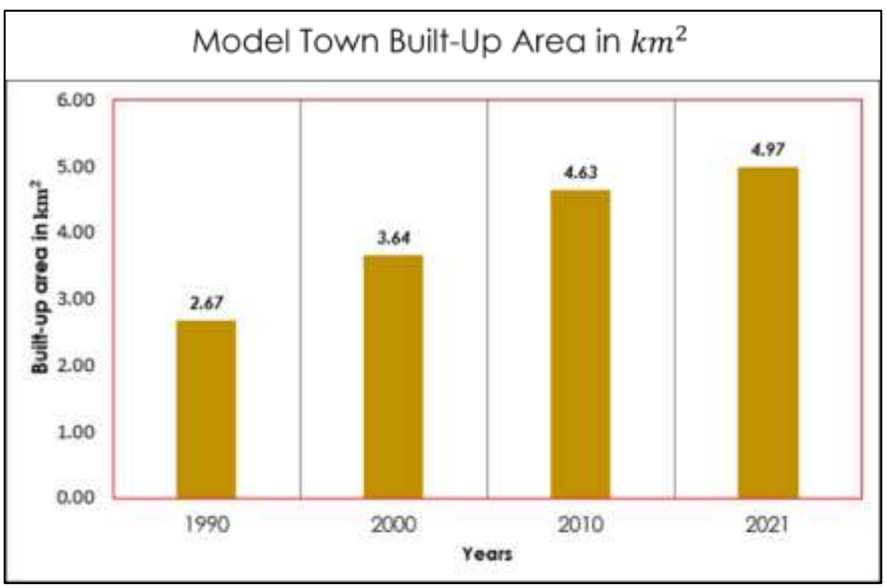

Figure 9: Built-up land of Model Town in the years 1990, 2000, 2010 and 2021

The LST and built-up area have increased parallel to each other from 1990 to 2021 in Lahore (Figure 3 and Figure 8) and Model Town (Figure 6 and Figure 9). (Javid et al., 2021) in his study found that the urbanization process causes the impervious surface to absorb heat quickly but emit it slowly, which is what causes the high surface temperature. LST rises when vegetation and green spaces gradually decrease. Lahore has only 3% green areas, which is well below the global benchmark that calls for allocating a minimum of 25% to 30% of metropolitan area to green open space (Imran & Mehmood, 2020). Using surveys of precipitation from

Lahore residents, (Shirazi & Kazmi, 2016) discovered that the rapid expansion of residential societies and vast infrastructure, which took place over green spaces and agricultural fields, is to account for the city's massive loss of vegetation.

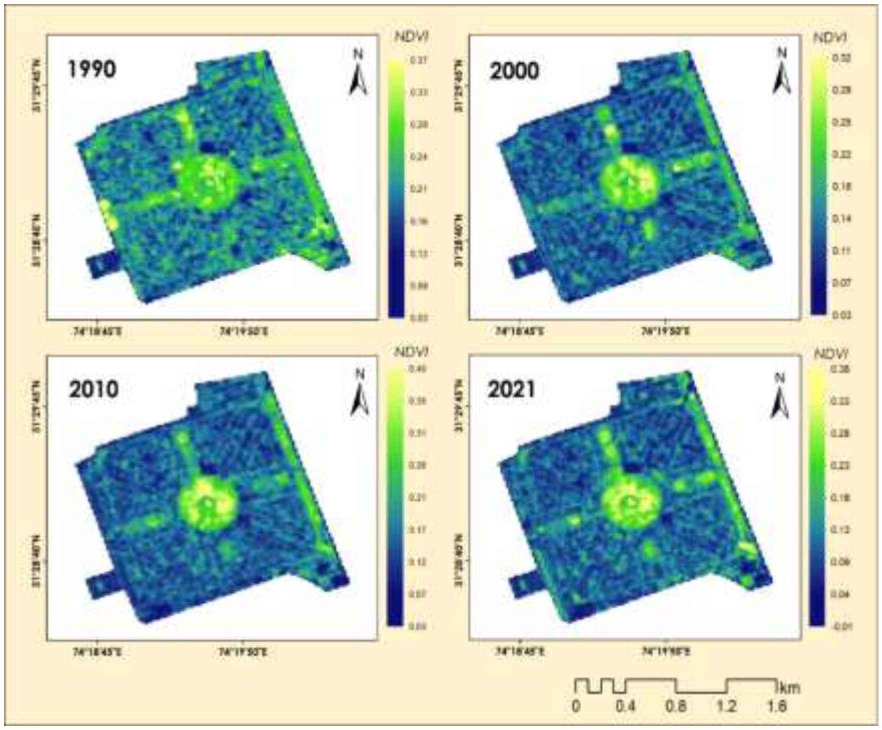

Figure 10: NDVI of Model Town for 1990, 2000, 2010 and 2021

Table 5: Descriptive statistics for NDVI of Model Town

Years	Min	Max	Mean	Std Dev.	Vegetative Area (km^2)
1990	0.039	0.372	0.138	0.043	3.98
2000	0.035	0.326	0.118	0.044	2.35
2010	0.033	0.405	0.135	0.055	2.09
2021	-0.008	0.385	0.125	0.058	1.74

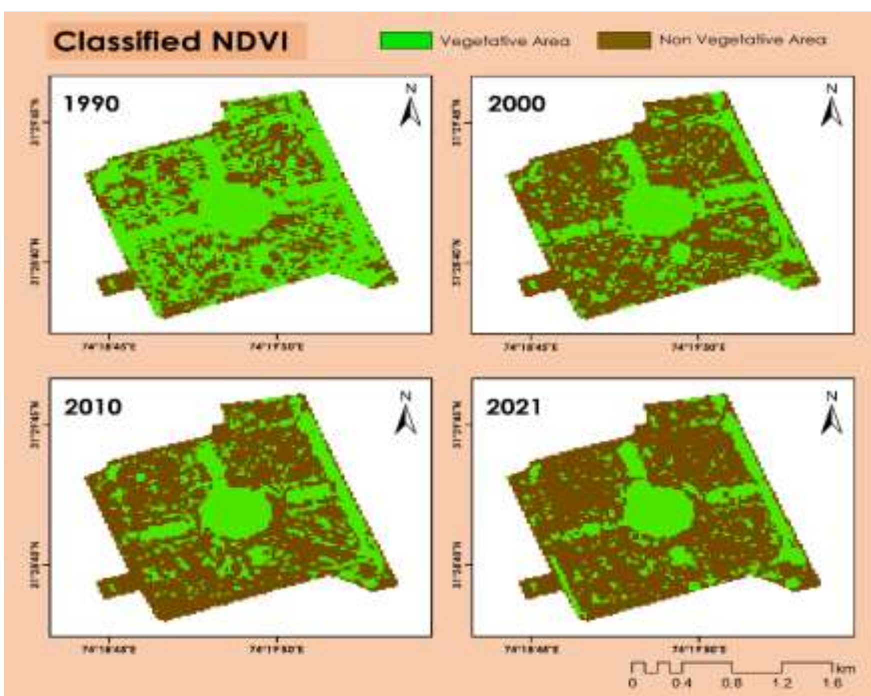

Figure 11: Classified NDVI of Model Town as vegetative and non-vegetative area

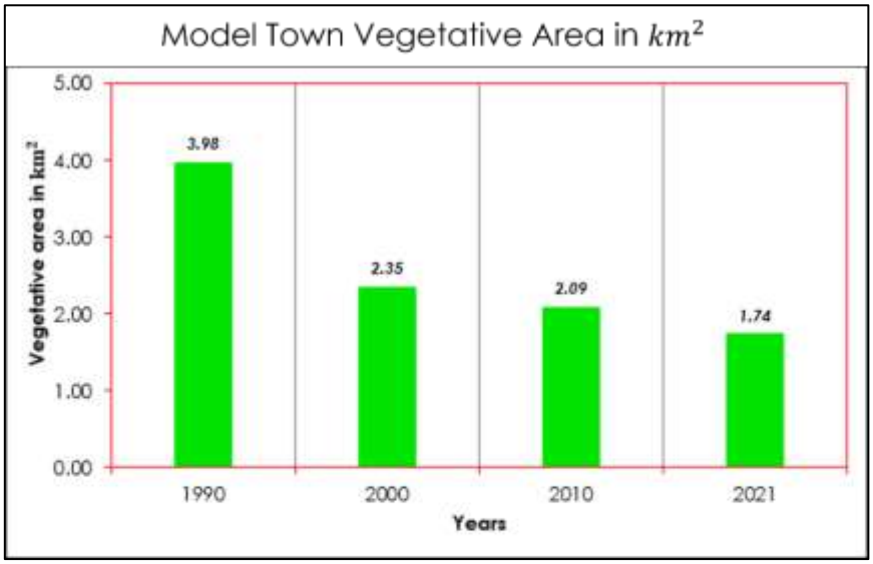

Figure 12: Vegetative Area of Model Town in the years 1990, 2000, 2010 and 2021

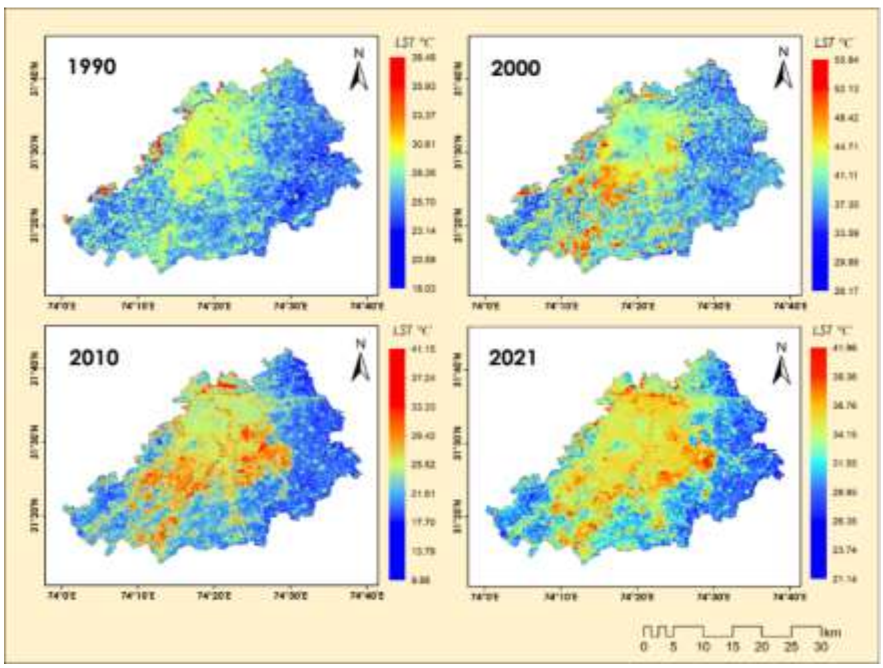

Figure 13: Land Surface Temperature (LST) of Lahore for 1990, 2000, 2010 and 2021

Table 6: Descriptive statistics for Land Surface Temperature (LST) of Lahore

Years	Min	Max	Mean
1990	18.03	38.48	25.72
2000	26.17	55.84	37.85
2010	9.88	41.15	25.06
2021	21.14	41.96	29.17

Tables 4 and 5 also show the minimum, maximum, and mean LST observed for the Lahore and Model Town, respectively. the highest mean value of LST 30.62℃ and the lowest mean value of LST 27.20℃ is recorded in the year of 2021 and 2010 for Model Town, respectively. The rise of LST is due to the major contribution of built-up land (Bokaie et al., 2016) as it is observed that in 1990 when built-up land was 455.45 km^2 and 2.667 km^2 for Lahore and Model Town, the mean LST was 25.72℃ and 27.49℃ for Lahore and Model Town, respectively. However, the built-up area increased to 807.40 km^2 and 4.969 km^2 in 2021, the mean LST increased to 29.17℃ and 30.62℃ for Lahore and Model Town, respectively. These results confirm the direct relationship between urban land and LST (Ullah et al., 2019), which is in line with a study conducted by (Xiong et al., 2012).

Due to the various reflectance characteristics of LULC (Nasar-u-Minallah, 2019), changes in land use and land cover have a considerable impact on land surface temperature (Goksel et al., 2006). The LST results (Figures 8 and 9) show that, during the past 30 years, the maximum and mean LST have increased steadily while the lowest LST has some variations. In previous studies carried out in Lahore and other regions of South Asia, the rise in LST was also noted (Javid et al., 2021; Imran and Mehmood, 2020; Hassan et al., 2021; Dilawar et al., 2021). This may be due to anthropogenic materials used in urban expansion, such as high-rise buildings, asphalt, and concrete (Bokaie et al., 2016).

Table 7: Descriptive statistics for Land Surface Temperature (LST) of Model Town

Years	Min	Max	Mean
1990	25.50	30.22	27.49
2000	26.02	32.37	28.74
2010	24.42	31.09	27.20
2021	27.60	34.03	30.62

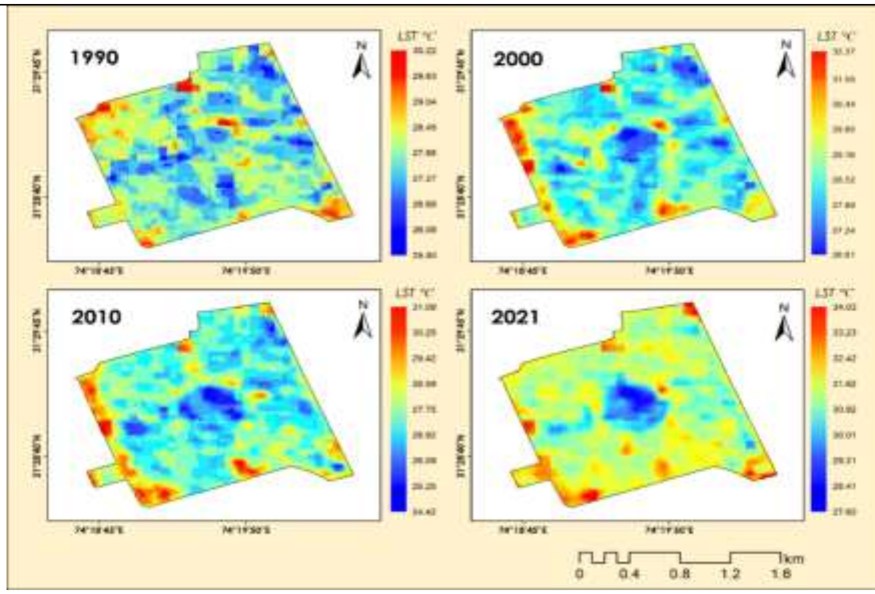

Figure 14: Land Surface Temperature (LST) of Model Town for 1990, 2000, 2010 and 2021

4.3. Land Use and Land Cover Change Detection

Figure 16 and 17 shows the total Land Use and Land Cover change occurred during 1990 to 2021 for different time periods, respectively. As indicated in Figure 16, the change in the NDBI over the model town for the periods of 1990-2000, 2000-2010, 2010-2021, and overall, 1990-2021 has been observed. From 1990-2000 the maximum significant positive change is observed to be in the central left pocket in the model town, indicating the increase in the built-up land. Around 251 km^2 area has observed the positive change in NDBI during 1990-2000, 36 km^2 in 2000-2010, 7.2 km^2 in 2010-2021 and overall, 91.8 km^2 from 1990-2021. Also, the central park and recreational green region in the heart of the model town have shown a negative change indicating the fact that the vigor of vegetation in this patch has increased, which can also be checked in Figure 17, showing the change in the NDVI over the various periods between 1990-2021. The maximum significant positive change in the NDVI has been observed during 2000-2010, showing the increase in the vigor of vegetation mostly in the central part of the model town. Around 18 km^2 area has observed the positive change in NDVI during 1990-2000, 155 km^2 in 2000-2010, 61 km^2 in 2010-2021 and overall, 135 km^2 from 1990-2021.

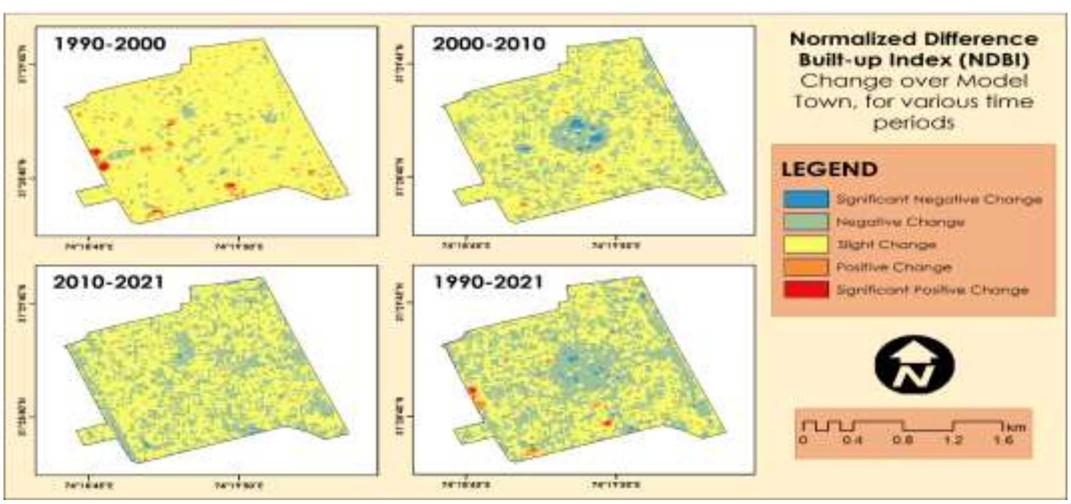

Figure 15: NDBI Change over Model Town during various time periods

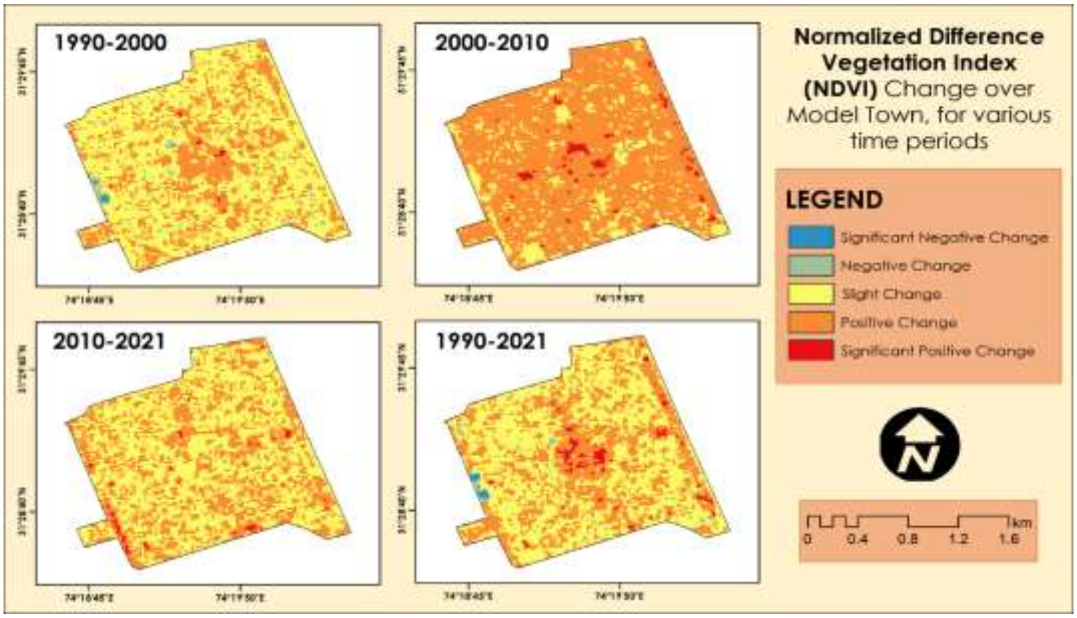

Figure 16: NDVI Change over Model Town during various time periods

5. Conclusion

Land Use change analysis has been performed over Lahore and Model Town by utilizing the Landsat 5 TM and Landsat 8 OLI data from 1990 to 2021, by taking the individual years as 1990, 2000, 2010, and 2021. The NDBI index over the region of Lahore and Model Town have been calculated by using the NIR and SWIR bands of TM and OLI. After calculating NDBI, the index-based classification technique was utilized to classify the NDBI result image into two classes as built-up land and non-built-up land for Lahore and Model Town. The highest built-up area has been observed in the year of 2021 with a total 807.40 km^2 and comparatively low as 455.45 km^2 in 1990 in Lahore. On the contrary, the highest built-up area was mapped in 2021 as 4.969 km^2, and lowest as 2.667 km^2 in 1990 for Model Town. The percentage increase in the built-up land over Lahore and Model Town has been calculated to be 43.59 % and 46.32 % respectively. with the highest change in percentage increase to be found from 1990 to 2000 with an overall increase equal to 28.25 % for Lahore and 26.74% for Model Town. It is observed that in 1990 when built-up land was 455.45 km^2 and 2.667 km^2 for Lahore and Model Town, the mean LST was 25.72 ℃ and 27.49 ℃ for Lahore and Model Town, respectively. But, as the built-up area increased to 807.40 km^2 and 4.969 km^2 in 2021, the mean LST increased to 29.17℃ and 30.62℃ for Lahore and Model Town, respectively. The LST results show that, during the past 30 years, the maximum and mean LST have increased steadily while the lowest LST has some variations. The highest vegetative cover area was observed in 1990 1045.76 km^2 and 3.98 km^2 over Lahore and model town respectively. On the other hand, the lowest vegetative area has observed in 2021 as 918.72 km^2 and 1.74 km^2 over Lahore and Model Town respectively. Around 13.82% and -128.47% of the vegetative area decreased over 30 years (1990-2021) for Lahore and Model Town respectively.

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