URBAN EXPANSION AND ITS INFLUENCE ON LAND SURFACE TEMPERATURE: A CASE STUDY OF PATNA CITY, INDIA

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ABSTRACT

Rapid urbanization in developing countries has significant implications for local climate and environmental conditions. This study examines land use/land cover (LULC) changes and their impact on land surface temperature (LST) in Patna, India from 1988 to 2022 using Landsat imagery and geospatial techniques. Rapid urbanization in developing cities can significantly alter local climate, but the dynamics in Patna were not well understood. Using supervised classification and thermal band analysis, the research quantified LULC transformations and LST changes over 34 years. Results show dramatic urban expansion, with built-up area increasing from 38 % to 80 % of the total area, while vegetation cover decreased from 44 % to just 7 %. These changes corresponded with an overall increase in LST, with maximum temperatures rising by 1.06°C and minimum temperatures by 6°C. Strong correlations were found between LST and spectral indices like NDVI (negative) and NDBI (positive). The study reveals accelerated urban growth and temperature increases, especially after 2005, highlighting the need for sustainable urban planning strategies to mitigate heat island effects and improve thermal comfort in Patna. This research provides valuable baseline data for understanding urbanization impacts on local climate in rapidly growing Indian cities.

Keywords: Land use/land cover (LULC), Land surface temperature (LST), Urbanization, Remote sensing, Patna (India), Urban heat island

INTRODUCTION

Land use/cover (LULC) changes are the primary causes of biogeochemical processes that lead to regional and global climate change (Luyssaert *et al*., 2014; Song *et al*., 2020; Ke *et al*., 2021; Xu *et al*., 2022; Anupriya & Rubeena, 2024). LULC change results from the complex interactions between people and their physical settings. Human-induced changes and decisions have altered around three-quarters of the earth's surface over the past millennia (Luyssaert *et al*., 2014; Shukla *et al*., 2019). Anthropogenic LULC variations are primarily caused by population expansion, migrations from rural to urban areas, industrialization-induced urban development, and agricultural deforestation. The last decade witnessed a global loss of 0.8 million km² of forest land. In contrast, globally agricultural land fell by almost 3 percent due to a 6 percent decline in permanent pastures and meadows and a 5 percent rise in crops. In developing nations, natural land is increasingly being converted into urban built-up areas (Winkler *et al*., 2021). As a response of these conversions, LULC has been reported as one of the major factor contributing to the rise in land surface temperature (LST) of urban centres (Ayanlade *et al*., 2021; Khan *et al*., 2024). However, the urban environment and residents might be negatively impacted by the drastic change in land use and land cover (LULC). Macro-level effects have been shown in studies, including habitat loss (Seto *et al*., 2012), the heat island effect (Zhao *et al*., 2016), and a deterioration in the quality of the air and water (Shao *et al*., 2006). Because poor nations have fewer resources, they need to be equipped to address these social and environmental consequences (Cohen, 2006). Studying LULC changes, urban growth and its environmental impacts in emerging countries is therefore very important.

The form and content of the urban land surface alter as a result of the widespread conversion of natural land into built-up areas. The reduction of vegetative cover and increase in the impermeable layer resulting from the physical expansion of urban centers causes an increase in the land's thermal inertia, changes in evapotranspiration, and heat output from human energy usage (Nastran *et al*., 2019; Song *et al*., 2020). An obvious illustration of man-made climate change is the urban heat island effect, which causes cities to experience warmer temperatures than their rural environs (Nastran *et al*., 2019). This phenomenon endangers ecosystem services and the sustainable productivity of biomes (Luck and Wu, 2002).

Estimating LST using satellite imagery, such as Landsat or MODIS, is a common method for defining urban heat zones (Weng, 2009; Fu & Weng, 2016; Tran *et al*., 2017). In recent years, there has been growing concern about LST in urban centers and its associated effects on human health globally. The Intergovernmental Panel on Climate Change (IPCC) highlighted in 2001 that extreme weather episodes could lead to changes in health, such as increased heat stress and disease. According to a UN assessment, 54 percent of the world's population lives in cities, a number expected to rise to nearly 75 percent by 2050 (United Nations, 2014). Understanding microclimatic changes in cities and developing scientific adaptation strategies are critical aspects of sustainable urban development (Nastran *et al*., 2019).

Remote sensing (RS) and geographical information system (GIS) techniques allow efficient mapping of urban areas, simulation of urban expansion, and understanding of dynamic LULC changes (Bhagyanagar *et al*., 2012; Kimuku & Ngigi, 2017; Aboelnour and Engel, 2018). Conventional surveying techniques and land-based observation help observe dynamic LULC changes. However, satellite data provides more geographical distribution information, saving time and money (Abdulaziz *et al*., 2009). Remote sensing algorithms can more efficiently estimate LST and LULC from the same datasets when they combine multispectral bands with thermal infrared bands from Landsat pictures (TM, ETM+, OLI, and TIRS). Compared to MODIS (since 1999) and ASTER (since 2000), the long-term temporal range of Landsat data (Landsat-4/5 TM since 1980) offers seasonal and decadal analysis at a better geographic resolution (Petropoulos *et al*., 2016; Shimoda & Kimura, 2018). Due to high spatial resolution, broader swath, and long-term data availability, Landsat data was employed in this study.

Numerous studies have been conducted worldwide to understand the impact of LULC changes on climate change (Mahmood *et al*., 2010; Dunn *et al*., 2011; Nayak & Mandal, 2012; Dong *et al*., 2019; Gogoi *et al.,* 2019). The association between shifting LULC and

LST has been the subject of several global studies (Weng, 2001; Chen *et al*., 2006; Xian & Crane, 2006; Kayet *et al.*, 2016; Zhang & Sun, 2019). In India, scholars have examined LULC variations and their effects on LST dynamics in cities such as Mumbai (Sahana *et al*., 2019), Pune (Gohain *et al*., 2021), Delhi (Kumari *et al*., 2018), Kolkata (Biswas & Ghosh, 2022), Chennai (Chanu *et al*., 2021), Hyderabad (Chakraborti *et al*., 2019), Lucknow (Shukla & Jain, 2021), Thiruvananthapuram (Anupriya & Rubeena, 2024), Gaya (Omar & Kumar, 2021), and Ramnagar (Rawat *et al*., 2013). Mishra & Rai (2016) analyzed LULC changes in the Patna district and predicted future land use patterns using Markov chain analysis. Chettry & Surawar (2021) assessed urban sprawl in major Indian cities, including Patna, using remotely sensed data. Ahmad *et al*. (2023) investigated LULC and LST in Patna City using Indian Remote Sensing Satellite (IRS) data. However, limited work has been done on Patna City using Landsat imagery. This study aims to bridge this gap by analyzing the LULC change dynamics and its impact on LST in Patna City, Bihar, India.

While extensive research has been conducted on the relationship between LULC changes and LST in major metropolitan areas, medium-sized cities like Patna have received far less attention. Patna, the capital of Bihar and one of the fastest-growing cities in eastern India, has experienced rapid urbanization over the past few decades, with built-up areas increasing by over 105 % from 1988 to 2022. This expansion, driven primarily by rural-to-urban migration, has led to significant reductions in vegetation cover, likely contributing to the rise in LST. However, despite these substantial changes, few studies have specifically focused on how urban growth in Patna affects LST and contributes to the broader environmental challenges facing the city.

This study addresses these gaps by utilizing medium-resolution, long-term Landsat data to analyze LULC changes and their influence on LST in Patna over a 34-year period (1988-2022). By focusing on a mid-sized city that is often overlooked in urban climate studies, this research offers valuable insights into the relationship between urban growth and temperature dynamics in rapidly developing regions. Moreover, the study examines the correlation between LST and spectral indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-Up Index (NDBI), providing a more deeper insights into how different land cover types contribute to temperature variations. This novel focus on Patna’s urbanization patterns not only advances the understanding of LULC-LST interactions but also offers policy-relevant findings that could inform sustainable urban planning in similar cities.

STUDY AREA

Patna, the capital city of Bihar, India, is situated on the southern bank of the Ganges River at 25° 37' N latitude and 85° 10' E longitude. As the largest city in Bihar and the 19th largest urban agglomeration in India, Patna spans an area of approximately 108.75 square kilometers and had a population of around 1.7 million according to the 2011 Census (Census of India, 2011). However, more recent estimates from the 2021 Census project a population exceeding 2.5 million, reflecting the city's rapid urban growth and increasing population density. Patna's urban landscape is characterized by its historical significance, diverse socio-economic activities, and a growing industrial and educational base, which have contributed to its rapid expansion over the last few decades.

Administratively, Patna is governed by the Patna Municipal Corporation (PMC), which is divided into six administrative circles: Patna City, Bankipur, Patliputra, Kankarbagh, Azimabad, and New Capital circles. The city's strategic location, along with its role as a regional hub for commerce and education, has attracted substantial rural-to-urban migration since the 1980s, leading to significant, often unplanned, urban expansion. This expansion has resulted in a marked transformation of land use patterns, particularly the conversion of agricultural and vegetated areas into built-up zones, contributing to environmental challenges such as increased land surface temperature (LST), reduced green cover, and the degradation of air and water quality.

Patna experiences a humid subtropical climate with average annual temperatures of approximately 26 °C. The hottest month is May, with an average temperature of 32.4 °C, while January is the coldest, averaging 17.2 °C. The city receives annual rainfall of 1000-1100 mm, with about 80 % occurring during the monsoon season. Recent urban expansion, combined with the city's climatic conditions, has exacerbated environmental stress, including the urban heat island (UHI) effect, rising LST, and increased vulnerability to flooding due to reduced permeable surfaces.

Fig. 1: Location of the Study Area

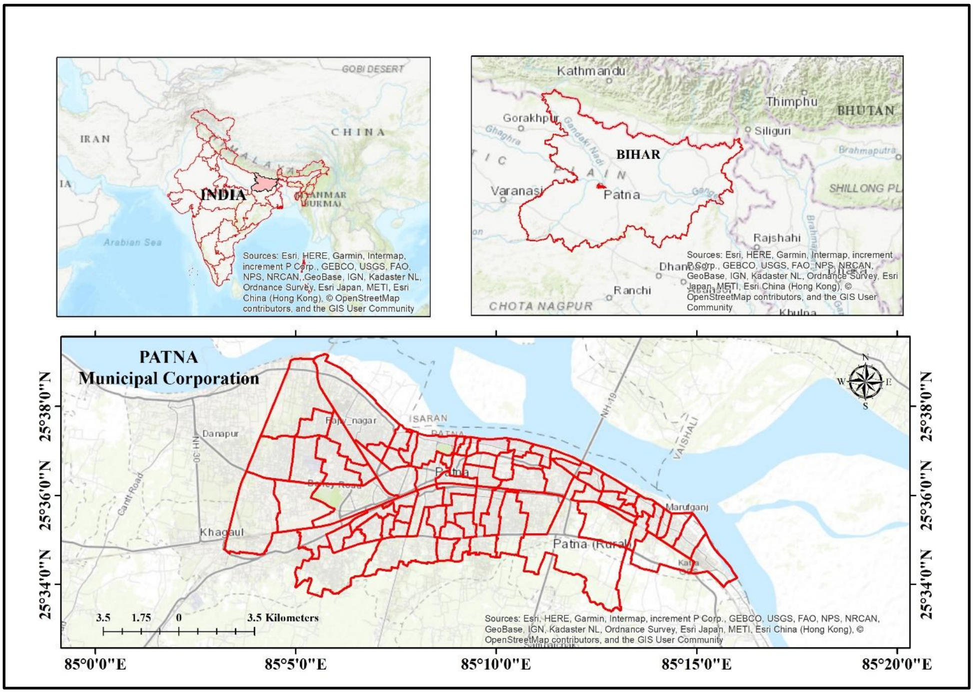
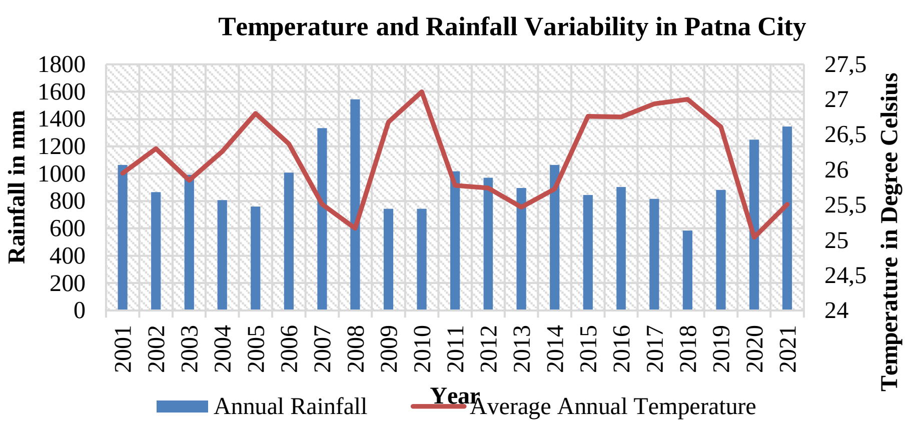


Fig. 2: Temperature and Rainfall Variability in Patna City



DATABASE AND METHODOLOGY

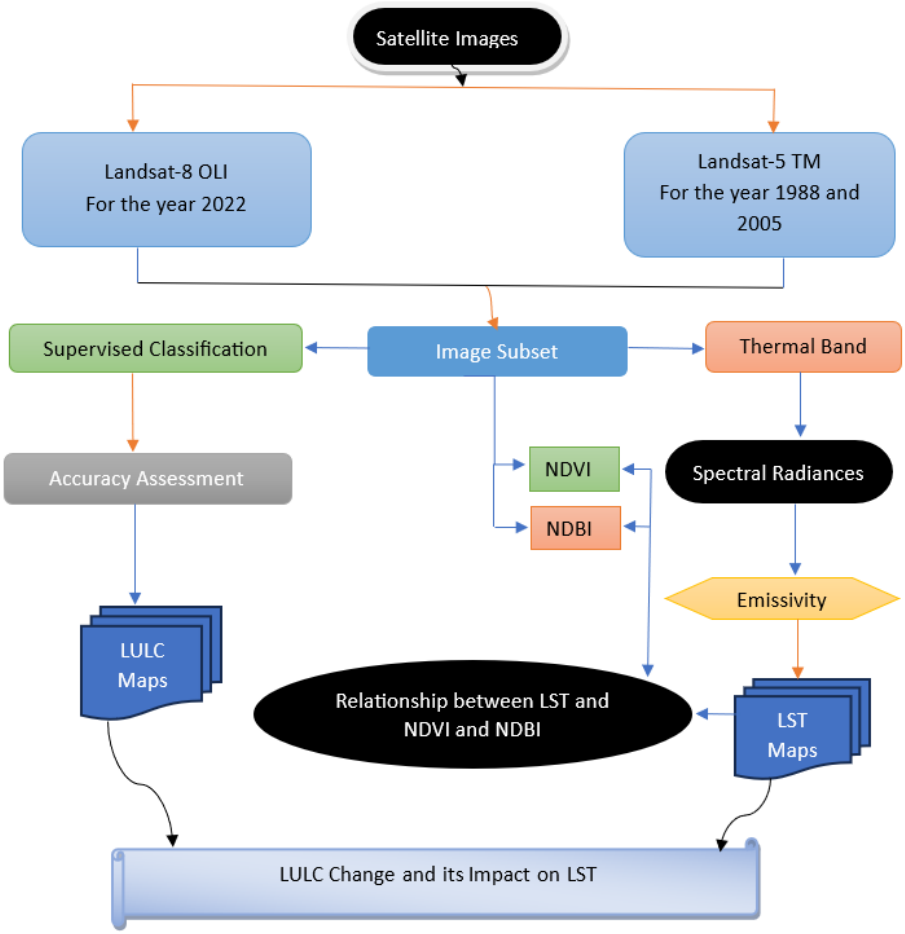
Data Used

In this study, Landsat images from three different periods (1988, 2005, and 2022) of Patna city have been acquired to systematically quantify land use/cover patterns and their impact on the distribution of land surface temperature (LST). These Landsat images were also used to highlight changes in land use patterns and to compute LULC indices including the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-Up Index (NDBI) for the years 1988, 2005, and 2022. For the years 1988 and 2005, images from the Landsat 5 satellite; and for the year 2022, images from the Landsat 8 satellite with less than 5 percent cloud cover were searched from the United States Geological Survey (USGS) website (http://glovis.usgs.gov/). And from the obtained results, images with zero cloud cover were downloaded for the study. To reduce the impact of seasonal fluctuations, all satellite images were downloaded for the same month (Table 1). ArcGIS 10.5 software is used for deriving land use, LST, NDVI, and NDBI maps of the study area for the study periods. The relationship of LST with NDVI and NDBI is assessed by regression analysis in MS Excel software. However, Fig. 3 presents the entire methodological approach used in the study.

Table 1: Details of the database used in the study

Year	Satellite	Date of Acquisition	Sensor	Path/Row	Cloud Cover
1988	Landsat-5	3rd April	TM	141/42	< 5 Per cent
2005	Landsat-5	2nd April	TM	141/42	< 5 Per cent
2022	Landsat-8	2nd April	OLI	141/42	< 5 Per cent

Fig. 3: Schematic illustration of the methodology used in the study



LULC Classification and Accuracy Assessment

The LULC maps of the Patna Municipal Corporation (PMC) were prepared for the years 1988, 2005, and 2022. These maps were created using supervised classification by employing the maximum likelihood algorithm, which has been demonstrated to be an effective classification system for medium-resolution images (Iqbal & Iqbal, 2018; Vivekananda *et al*., 2020). This algorithm operates based on Bayes' theorem (Anupriya & Rubeena, 2024). Five broad land use categories were identified: Built-up area, Water body, Bare land, Agricultural land, and Vegetation cover.

To ensure the accuracy and reliability of the classified LULC maps, an error matrix of square matrices organized in a row and column configuration was utilized. This technique is widely accepted for calculating accuracy assessment (Choudhary *et al*., 2019; Pandey *et al*., 2022; Tariq *et al*., 2022; Anupriya & Rubeena, 2024). Random stratified sampling was systematically carried out for each class, and the following accuracy evaluation produced several crucial metrics: producer's accuracy, user's accuracy, total accuracy, and Kappa coefficient, which provided a thorough analysis of the classification outcomes.

Estimation of NDVI and NDBI

Normalized Difference Vegetation Index (NDVI): It is a vegetation index produced from satellite imagery widely used to evaluate green spaces. It is also beneficial in understanding urban environments as indicators of green cover (Mohammed *et al.*, 2019). Red and near-infrared bands of multispectral images are used in its calculation. The following equation is applied to obtain NDVI:

$$\mathrm{NDVI} = \frac{\mathrm{BNIR} - \mathrm{BRED}}{\mathrm{BNIR} + \mathrm{BRED}}$$

Where:

- BNIR = Near-infrared band (Band 4 of TM and ETM, and Band 5 of OLI), and
- BRED = Red band (Band 3 of TM/ETM, and Band 4 of OLI).

NDVI values range from -1 to 1, with negative values representing water bodies and values above 0.6 indicating dense vegetation.

Normalized Difference Built-up Index (NDBI): NDBI is a spectral index for estimating the size and dispersion of built-up and construction areas. The NDBI value ranges from -1 to +1 and is calculated using the following formula (Zha *et al.*, 2003):

$$\mathrm{NDBI} = \frac{\mathrm{BMIR} - \mathrm{BNIR}}{\mathrm{BMIR} + \mathrm{BNIR}}$$

Where:

- BMIR = Mid-infrared band (Band 5 of TM and ETM, and Band 6 of OLI), and
- BNIR = Near-infrared band (Band 4 of TM and ETM, and Band 5 of OLI).

Negative NDBI values represent water bodies, while values near +1 indicate very densely built-up areas. NDBI value close to zero represents vegetation cover.

Computation of LST

LST, a quantitative indicator of temperature differences at the boundary between land and atmosphere, suggests spatiotemporal changes in the land surface influenced by built-up areas, canopy cover, and soil temperatures (Nemani *et al.*, 1993). Band-6 of Landsat-5 TM, and Band-10 of Landsat-8 OLI are identified as thermal bands; they are used to estimate the LST. There are minor variations in the method used to calculate spectral radiance (Lλ) when extracting LST from Landsat TM and Landsat OLI. The following are the steps for LST extraction, which are described in depth in a number of publications (Asgarian *et al.*, 2015; Govind & Ramesh, 2019):

Step I: Conversion of Digital Number (DN) to Radiance/TOA Radiance (Lλ). The following formula is used to get the spectral radiance for images from Landsat 5 TM (band 6):

$$L\lambda = L_{\mathrm{MIN}}\lambda + \left[\frac{(L_{\mathrm{MAX}}\lambda - L_{\mathrm{MIN}}\lambda)}{(Q_{\mathrm{CALMAX}} - Q_{\mathrm{CALMIN}})}\right] \times (Q_{\mathrm{CAL}} - Q_{\mathrm{CALMIN}})$$

Where:

- Lλ = Spectral radiance
- Q_{CAL} = Quantized calibrated pixel values in DN
- Q_{CALMIN} = Minimum quantized calibrated pixel value (corresponding to $L_{\mathrm{MIN}}\lambda$) in DN

- QQ_{CALMAX} = Maximum quantized calibrated pixel value (corresponding to $L_{\mathrm{MAX}}\lambda$) in DN
- $L_{\mathrm{MIN}}\lambda$ λ = Spectral radiance scaled to QCALMIN
- $L_{\mathrm{MAX}}\lambda$ = Spectral radiance scaled to QCALMAX

Spectral radiance for Landsat-8 OLI images (band 10) is derived using:

$$L\lambda = M_L \times Q_{\mathrm{CAL}} + A_L$$

Where:

- $L\lambda$ = Spectral radiance
- M_L= Band-specific multiplicative rescaling factor (0.0003342)
- A_L = Band-specific additive rescaling factor (0.1)
- Q_{CAL} = Quantized and calibrated standard product pixel value

Step II: Transformation of Spectral Radiance to At-Satellite Brightness Temperature (BT). Using the thermal constants listed in the metadata file, the data is transformed from the digital number into radiance and then into brightness temperature (BT):

$$BT = \left[\frac{K2}{\ln\left(\frac{K1}{L_\lambda} + 1\right)}\right] - 273.15$$

Where:

- BT = At-satellite brightness temperature
- L_λ = TOA Spectral radiance
- K1 = Band constant 1
- K2 = Band constant 2
- 273.15 converts temperature from Kelvin to Celsius

Step III: Proportion of Vegetation (Pv). The proportion of vegetation is calculated using the NDVI:

$$Pv = \left(\frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{min}}}{\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}}\right)^2$$

Step IV: Emissivity Correction (Ɛ). Emissivity correction is calculated using:

$$Land\ Surface\ Emissivity\ (\varepsilon) = 0.004 \times Pv + 0.986$$

Step V: Calculation of Land Surface Temperature (LST)

$$LST = BT/\left[1 + \left\{\frac{\lambda \times BT}{\rho}\right\} \times \ln(\varepsilon)\right]$$

Where:

- BT is the brightness temperature in Kelvin
- λ = Wavelength of emitted radiance
- ρ = h×c/s
- h = Planck's constant
- s = Boltzmann constant
- c = Velocity of light
- Ɛ = Emissivity

RESULTS

Land Use/Land Cover Change Dynamics

The classified maps using the maximum likelihood algorithm for the years 1988, 2005, and 2022 reveal that, over the past 34 years (1988-2022), Patna Municipal Corporation (PMC) has experienced significant land use/land cover changes (Fig. 4). Continuous increasing trend in built-up area and continuous decreasing trend in vegetation cover have been observed in PMC in the study period. However, unidirectional changes (Like built-up area and vegetation cover) in land use patterns have not been shown by agricultural land, water body, and bare land (Table 2; Fig. 5).

Table 2: Land use/land cover change from 1988 to 2022

	1988		**2005**		**2022**	
LULC Class	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Water Body	126.16	1.19	68.82	0.65	82.87	0.78
Vegetation	4622.87	43.66	3836.13	36.23	744.00	7.03
Built-up Area	4023.27	37.99	4442.45	41.95	8414.97	79.47
Agricultural Land	1653.66	15.62	2081.78	19.66	1131.8	10.69
Bare Land	163.54	1.54	160.32	1.51	215.86	2.04
Total Area	**10589.5**	**100.00**	**10589.5**	**100.00**	**10589.5**	**100.00**

Among all land use classes, built-up areas, vegetation, and agricultural land have shown drastic changes throughout the study period, while bare land and water bodies were comparatively less dynamic. The total built-up area increased more than doubled during the study period, increasing from 38 % in 1988 to about 80 % in 2022. From 1988 to 2005 it increased by only 4 % but after 2005 a sharp increase was registered from 41.99 % to 79.47 %. Vegetation area decreased significantly, from 44 % in 1988 to only 7 % in 2022. It also shows a sharp decrease after 2005, it was 36.23 % of the total area in 2005 and decreased to only 7.03 % in the year 2022. Agricultural land registered more than a 4 % increase from 1988 to 2005 but then decreased by half from 2005 to 2022. Furthermore, more rapid LULC changes were registered after 2005 compared to the previous phase (1988 to 2005).

Fig. 4: Land use/land cover map of PMC for the years a) 1988, b) 2005, c) 2022

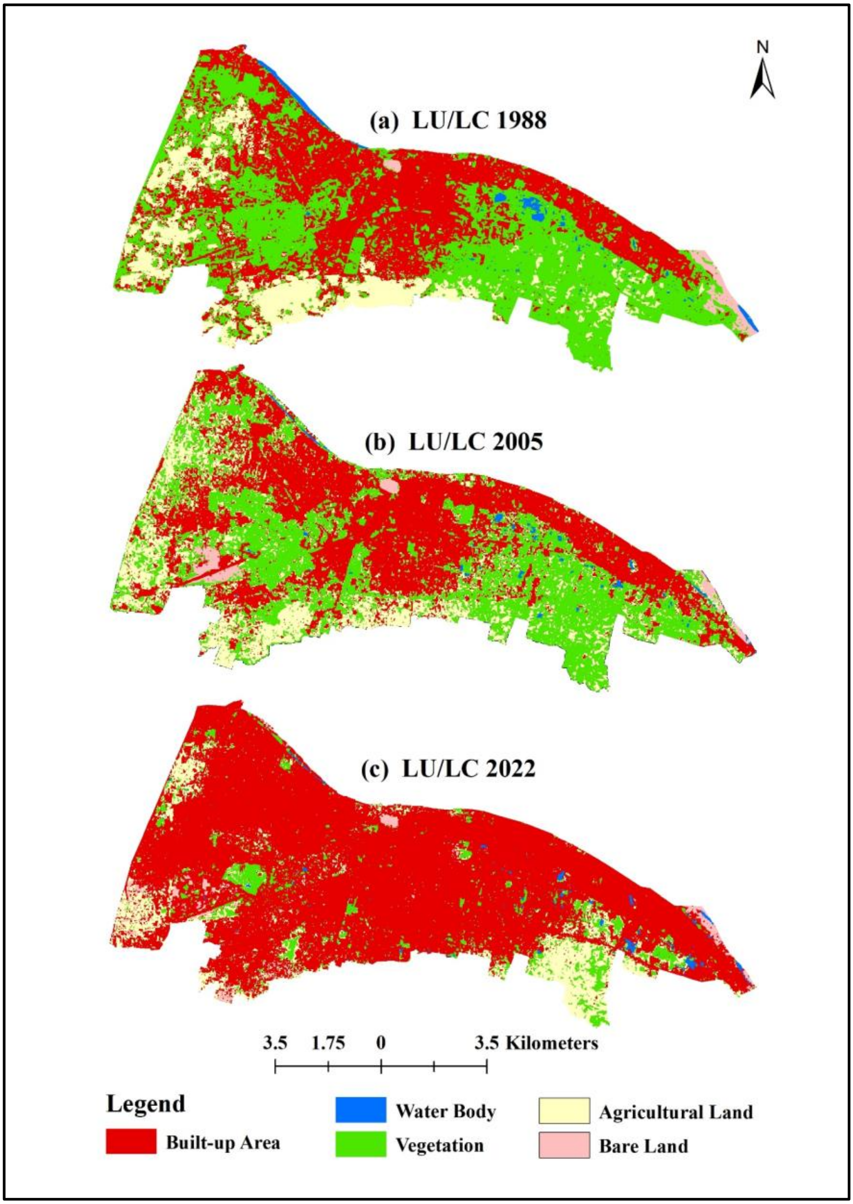
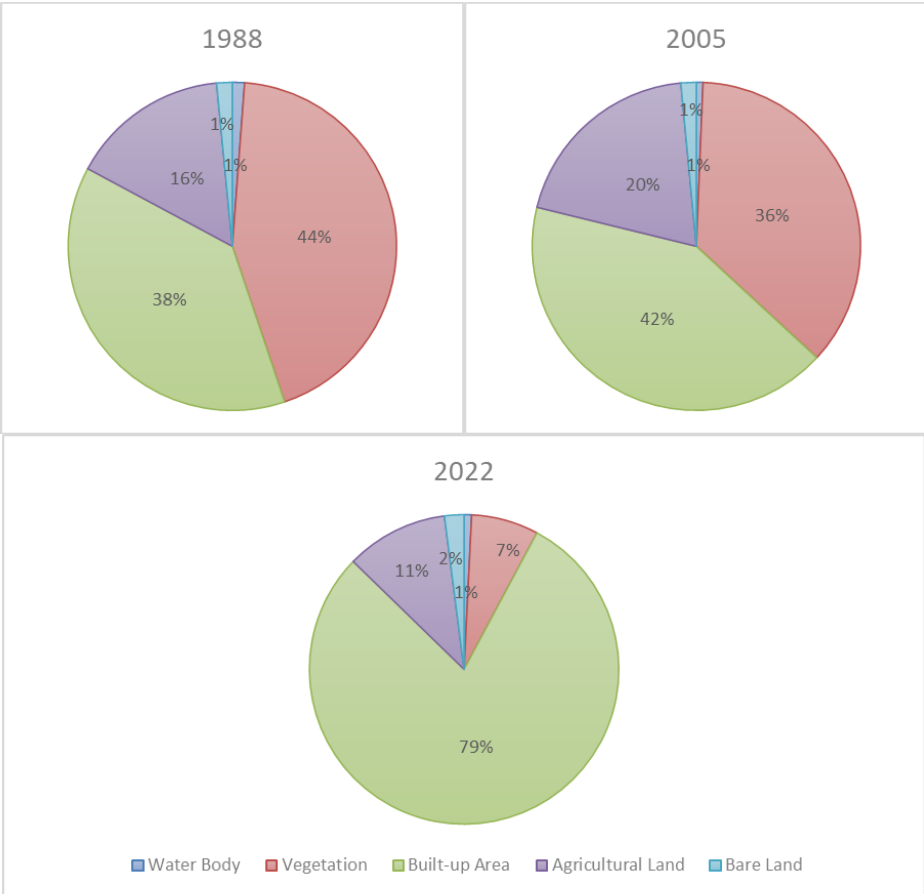


Fig. 5: Percentage distribution of land use dynamics in PMC for the years 1988, 2005, and 2022



Accuracy Assessment of the LULC Maps

To assess the reliability of the classified maps, user's, producer's, and overall accuracies, as well as the kappa coefficient, have been calculated using a confusion matrix. For this purpose, 118 random points for 1988, 118 for 2005, and 120 for 2022 were collected using Google Earth images to confirm the classified maps (Table 3).

The LU/LC map of both years 1988 and 2005 reflected same kappa co-efficient (0.91) and accuracy level (93 %). While the LU/LC map of the year 2022 have 94 % accuracy with 0.91 kappa co-efficient. The range of Kappa values is 0 to 1, where values nearer 1 denote more accuracy. A kappa value above 0.80 indicates excellent accuracy. Thus, all three LU/LC maps (1988, 2005, and 2022) have good accuracy agreements, with total accuracies over 80 % and kappa values greater than 0.85.

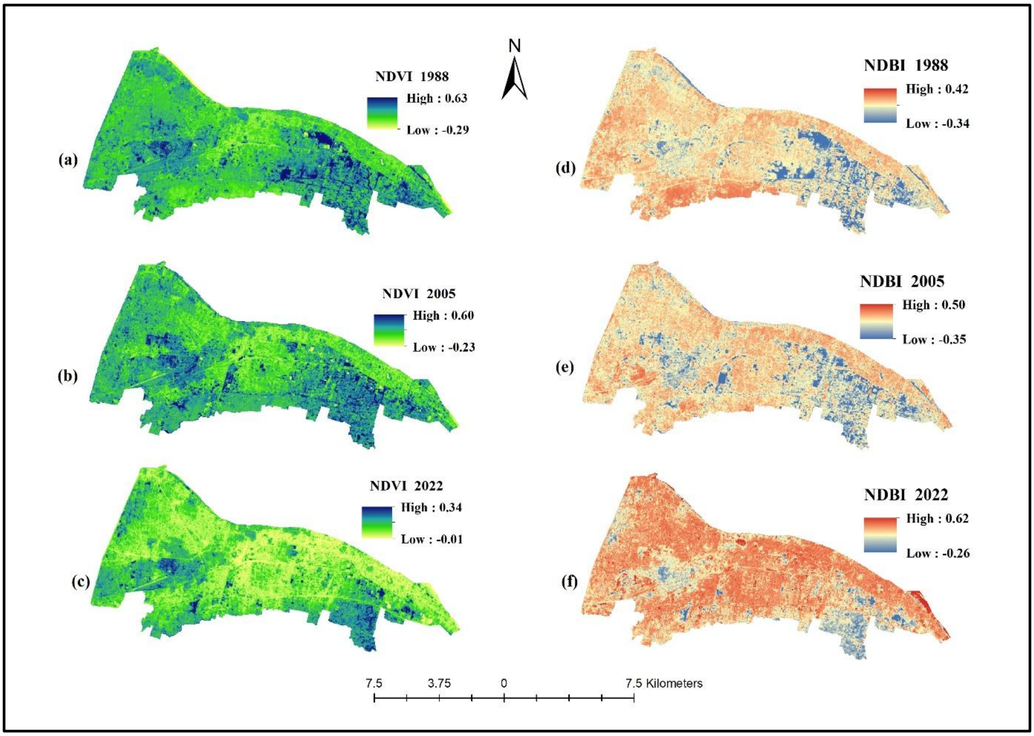
Table 3: Accuracy assessment of land use/land cover classes

For the Year 1988								
LULC Category	Water Body	Vegetation	Bare Land	Built-up Area	Agricultural Land	Total	User's Accuracy	***Overall Accuracy***
Water Body	9	1	0	0	0	10	90	***0.93***
Vegetation	1	40	1	2	0	44	91	
Bare Land	0	0	10	0	2	10	100	
Built-up Area	0	2	1	35	0	38	92	
Agricultural Land	0	0	0	0	16	16	100	
Total	10	43	12	37	16	118		
Producer's Accuracy	**90**	93	83	**94**	**100**			
Kappa Co-efficient	***0.91***							
For the Year 2005								
LULC Category	Water Body	Vegetation	Bare Land	Built-up Area	Agriculture Land	Total	User's Accuracy	***Overall Accuracy***
Water Body	9	0	0	0	1	10	90	***0.93***
Vegetation	0	32	0	3	1	36	88	
Bare Land	1	0	9	0	0	10	90	
Built-up Area	0	0	1	41	0	42	98	
Agriculture Land	0	0	0	1	19	20	95	
Total	10	32	10	45	21	118		
Producer's Accuracy	**90**	**100**	**90**	**91**	**90**			
Kappa Co-efficient	***0.91***							
For the Year 2022								
LULC Category	Water Body	Vegetation	Built-up Area	Agriculture Land	Bare Land	Total	User's Accuracy	***Overall Accuracy***
Water Body	9	0	0	1	0	10	90	***0.94***
Vegetation	0	10	0	0	0	10	100	
Built-up Area	0	2	74	0	3	79	94	
Agriculture Land	0	0	1	10	0	11	91	
Bare Land	0	0	0	0	10	10	100	
Total	9	12	75	11	13	120		
Producer's Accuracy	**100**	**83**	**99**	**91**	**77**			
Kappa Co-efficient	0.89							

Analysis of Spectral Indices

Remote sensing-based spectral indices such as NDVI, NDBI, NDWI, and NDBaI reveal the nature of the land surface. In this study, only NDVI and NDBI were retrieved, as the focus was on an urban area. The study showed an increasing trend of low NDVI and a decreasing trend of high NDVI throughout the study period in the Patna Municipal Corporation. In 1988, the NDVI range was 0.63 to -0.29; it was 0.60 to -0.23 in 2005, and 0.34 to -0.01 in 2022. Fig. 6 a-c clearly shows that areas with low NDVI are concentrated in the central and northern regions of the study area, while areas with high NDVI are densely distributed in the southeastern and southwestern margins of the PMC. It also reveals that the area under low NDVI is higher in 2022 compared to 2005 and 1988.

Fig. 6: Estimated NDVI (a-c), and NDBI (e-f) of the PMC



Spatio-temporal Variation of LST over the Patna Municipal Corporation (PMC)

Thermal bands of acquired Landsat data were used to generate Land Surface Temperature (LST) values for PMC for the years 1988, 2005, and 2022. As shown in Fig. 7, an increasing trend in LST has been observed in the study area throughout the study period; While Fig. 8 represents mean, maximum, and minimum LST of classified LU/LC classes for the year 2022. Highest mean and maximum LST was observed by builtup areas while highest minimum LST was observed by bare land. Whereas water bodies reflected lowest mean, maximum, and minimum LST. In 1988, the LST ranged from a low of 22.25°C to a high of 42.44°C; this increased to 27.09°C to 42.58°C in 2005, and 28.08°C to 43.50°C in 2022. The study reported an increase of 1.06°C in higher LST and about a 6°C increase in lower LST in the PMC during the entire study period from 1988 to 2022 (Fig. 9).

Fig. 7: Minimum, Mean and Maximum Temperatures for the Study Area

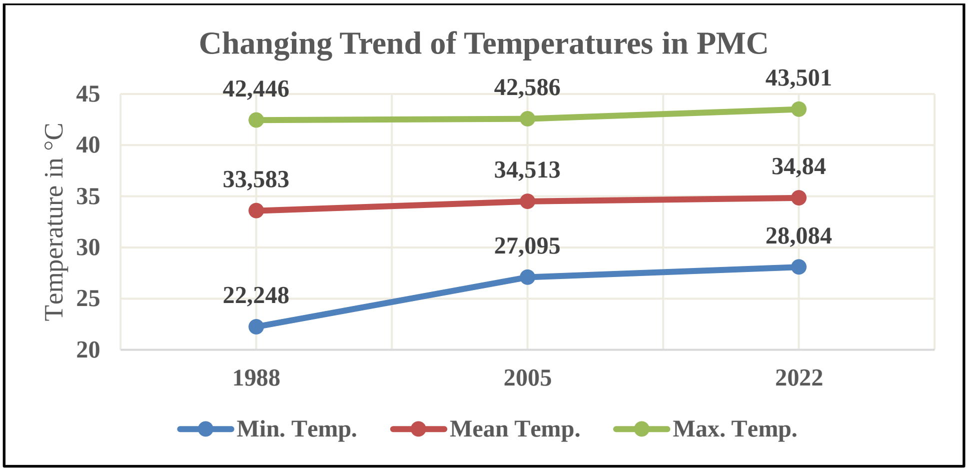


Fig. 8: Temperature Dynamics of LULC Classes of PMC for the Year 2022

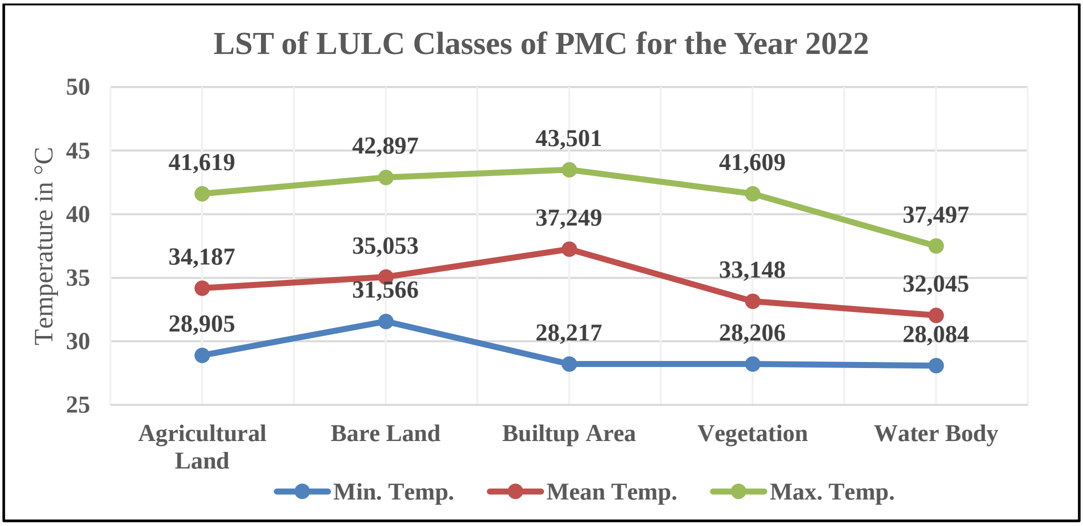


Fig. 9: LST dynamics in the PMC, a) 1988, b) 2005, c) 2022.

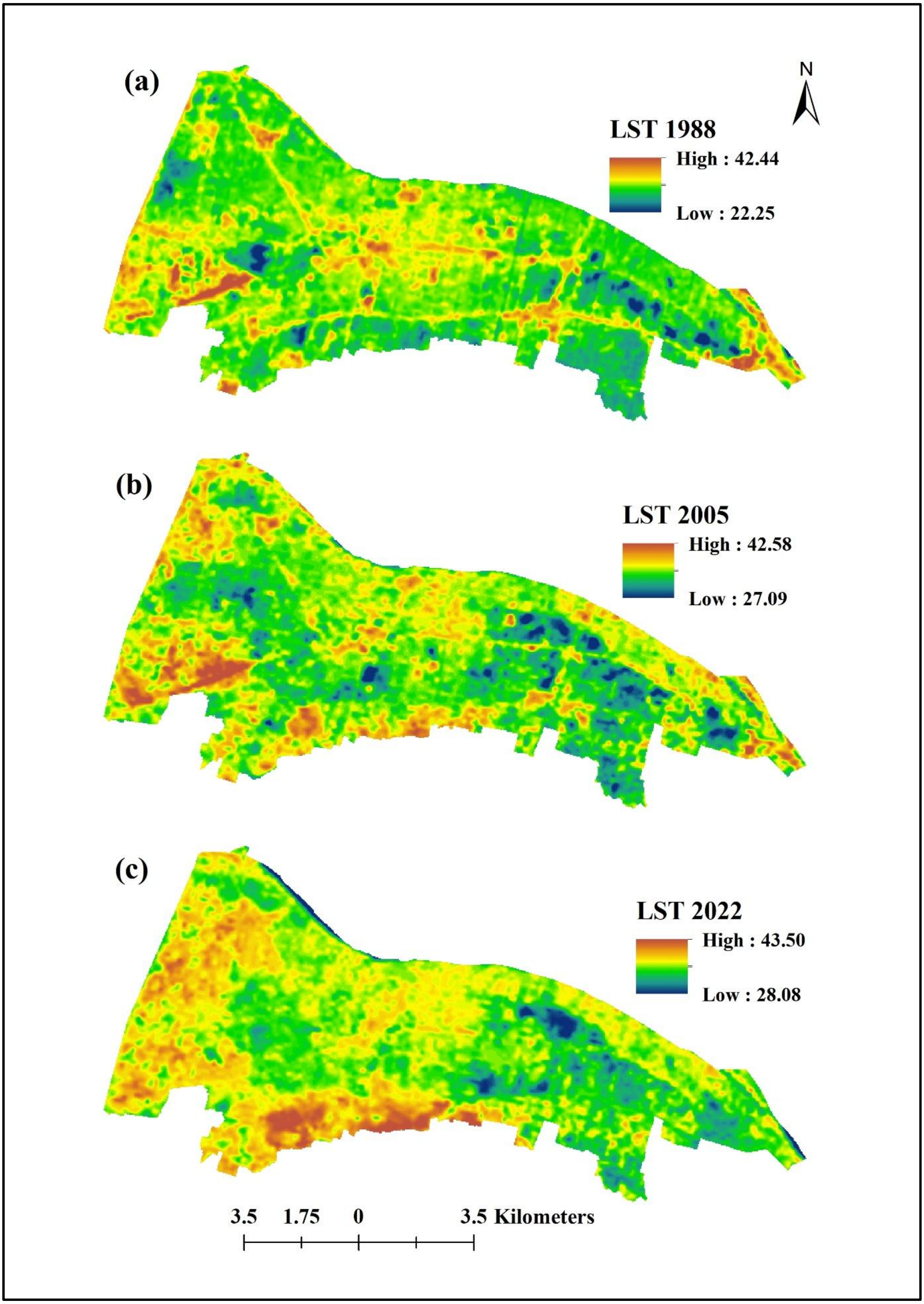
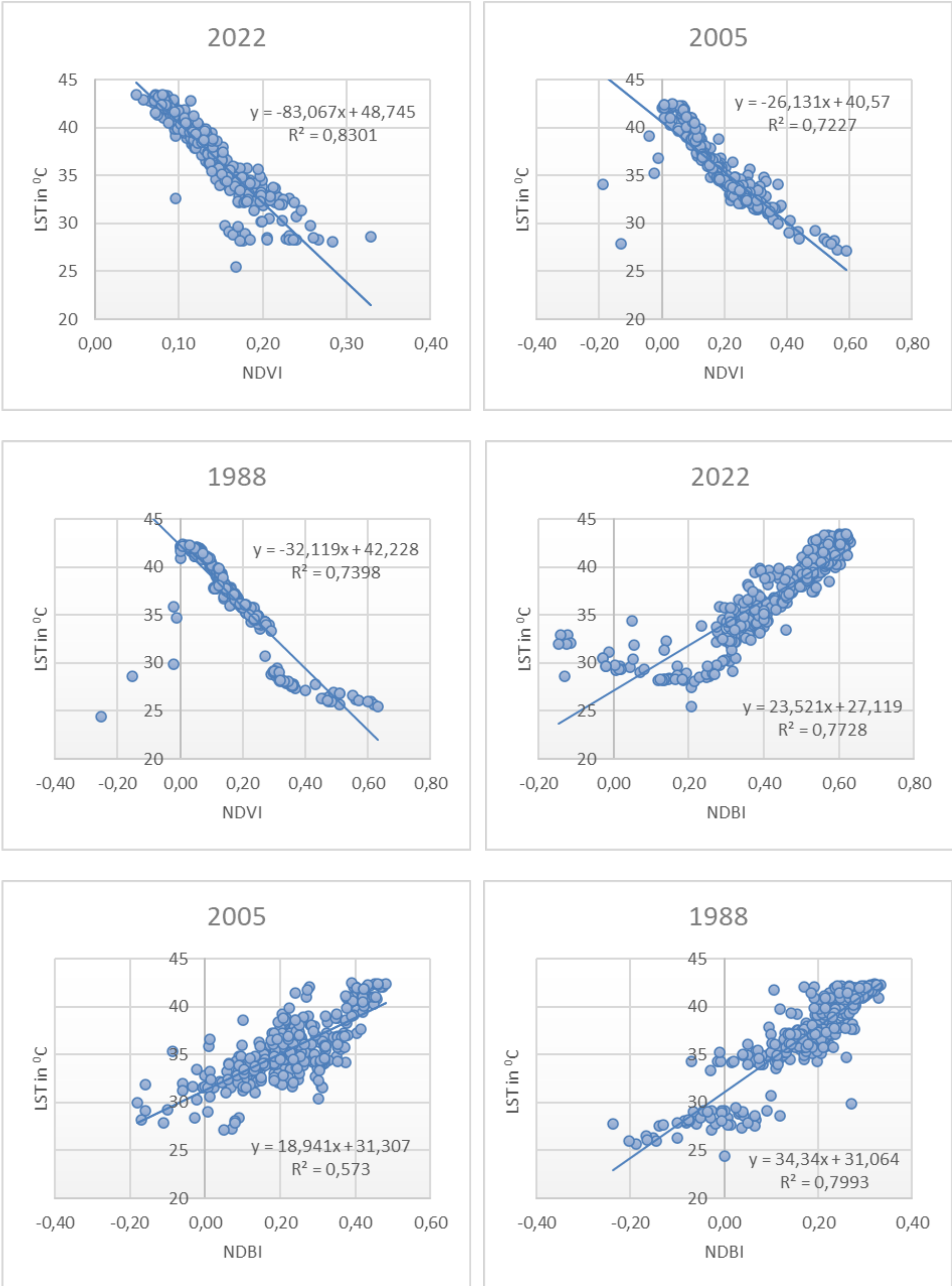


Fig. 10: Relationship of NDVI with LST and NDBI with LST for the Years 1988, 2005, and 2022



The association between LST with NDVI and LST with NDBI

To assess the relationship between LST with NDVI and NDBI, a total of 350 random points of all three (LST, NDVI, and NDBI) were generated for the years 1988, 2005, and 2022. The results of regression and correlation analysis between NDVI and LST reveal that in 1988, NDVI showed an R^2 value of 0.73 with a Pearson's correlation value (r) of -0.84; it was 0.72 and -0.85 in 2005. In 2022, NDVI represents an R^2 value of 0.83 with a correlation coefficient of -0.82. Similarly, NDBI reflects a strong positive relation with LST. In 1988, the R^2 value was about 0.80 with a correlation coefficient of 0.89, while in 2005, NDBI showed an R^2 value of 0.57 with a correlation coefficient of 0.76, and in 2022, NDBI revealed an R^2 value of 0.77 with a correlation coefficient of 0.88.

DISCUSSION

This study provides a detailed analysis of land use/land cover (LULC) changes and their impact on land surface temperature (LST) in Patna from 1988 to 2022. The findings show a 105 % increase in built-up areas and a 37 % decline in vegetation cover over the study period, contributing to significant temperature increases, with maximum LST rising by 1.06°C and minimum LST by 6°C. These results align with global urbanization patterns, where the replacement of vegetated land with impervious surfaces amplifies the urban heat island (UHI) effect (Seto *et al*., 2012; Zhao *et al*., 2016).

The sharp rise in built-up areas can be attributed to several factors, including rapid population growth, a large influx of migrant workers, and the development of infrastructure. Patna, as the capital of Bihar, experienced a significant population increase following the division of the state, with its population growing from 8.14 lakhs in 1981 to 16.83 lakhs in 2011 (Census of India, 2011). The city's strategic location, connectivity, and regional economic role have further fueled this expansion. Such demographic and infrastructural shifts have contributed to the expansion of built-up areas and the rise in LST, consistent with urbanization trends in other rapidly growing cities (Arulbalaji *et al*., 2020; Halder *et al*., 2022).

The results from spectral indices, such as the normalized difference built-up index (NDBI) and normalized difference vegetation index (NDVI), further illustrate the relationship between LULC changes and LST. NDBI values, representing impervious surfaces, increased from 0.42 in 1988 to 0.62 in 2022, while NDVI values, indicating green cover, showed a significant decline. This trade-off between built-up areas and vegetation cover reflects similar patterns in other tropical cities undergoing rapid urbanization (Arulbalaji *et al*., 2020; Andronis *et al*., 2022).

The regression models reveal a strong correlation between LST and the spectral indices NDVI and NDBI, with R^2 values exceeding 0.55 for each year. This indicates that NDVI and NDBI explain a large portion of the variability in LST across the study area (Peng *et al*., 2018). The negative correlation between NDVI and LST suggests that vegetation plays a significant role in moderating surface temperatures through processes like evapotranspiration and shading (Wang *et al*., 2018; Kafy *et al*., 2020). Conversely, the positive correlation between NDBI and LST highlights how urbanization and the increase in impervious surfaces contribute to higher surface temperatures. These findings echo those of previous studies on urban heat islands in tropical regions (Choudhury *et al*., 2019; Saha *et al*., 2021).

The spatial variability of LST in Patna is also notable, with areas along the western and southern boundaries showing significant increases in LST. These regions have undergone substantial LULC transformations, particularly the conversion of agricultural land and vegetation into built-up areas. As expected, the replacement of vegetated surfaces, which have high evapotranspiration rates, with impervious surfaces has contributed to higher LST in these areas. Such dynamics are consistent with findings from other studies that demonstrate how LULC changes affect surface energy fluxes and local climate conditions (Sadiq Khan *et al*., 2020; Das & Angadi, 2020).

The sharp rise in LST due to rapid urban expansion in Patna presents challenges for urban planners, particularly in mitigating the environmental consequences of unplanned growth. To address this, strategies such as urban greening and the adoption of cool roofs should be prioritized. Urban greening, including the development of green belts and the preservation of existing vegetation, could help lower LST by increasing evapotranspiration and providing shade (Mutani *et al*., 2020). Cool roofs, which reflect more sunlight and absorb less heat, could further mitigate the UHI effect in densely built areas (Khare *et al*., 2021). However, the successful application of these strategies in Patna requires careful consideration of local constraints, such as limited space for green infrastructure and the financial resources needed for retrofitting existing buildings. Public awareness campaigns and government incentives may help encourage the adoption of these sustainable practices.

The use of Landsat imagery and spectral indices like NDVI and NDBI has proven effective for assessing long-term LULC changes and their impacts on LST. However, the reliance on medium-resolution imagery limits the ability to capture fine-scale urban features, such as small green spaces and narrow streets, which may significantly influence LST. Future research should incorporate higher-resolution satellite data, such as Sentinel-2 or commercial sources, to improve spatial accuracy and provide more detailed insights into urban dynamics.

In addition, integrating socio-economic data, such as population density, income levels, and land ownership patterns, into the analysis would offer a more comprehensive understanding of the drivers and consequences of urbanization in Patna. This would enable planners to develop more targeted interventions that address both environmental and social challenges. Furthermore, adapting this study's methodology to other cities with varying climate conditions and urbanization patterns could provide valuable comparative insights and help refine urban heat mitigation strategies for different regional contexts.

This study offers valuable insights into the substantial impact of LULC changes on LST in Patna. The findings underscore the urgent need for sustainable urban planning strategies to mitigate the adverse effects of rapid urbanization. Drawing on successful strategies from other cities and tailoring them to Patna’s unique context can help urban planners develop more effective policies for managing urban growth while minimizing environmental impact. Future research should focus on incorporating higher-resolution imagery, more frequent data collection, and the integration of socio-economic variables to enhance our understanding of urbanization and its climate-related consequences in mid-sized cities like Patna.

CONCLUSION

This study highlights the significant role of urban expansion in driving increases in land surface temperature (LST) in Patna from 1988 to 2022. The findings reveal that the rapid growth of built-up areas, accompanied by a decline in vegetative cover, has contributed to an average increase in LST of 4.5°C. Areas with higher built-up density exhibited the most pronounced temperature rises, underscoring the importance of land use and land cover (LULC) dynamics in shaping local climate conditions.

The main takeaway from this study is that Patna's urban growth poses substantial challenges for environmental management, particularly in mitigating the urban heat island effect. To address this, urban planners should prioritize sustainable strategies, such as urban greening, the adoption of cool roofs, and more mindful land use planning tailored to the city's unique context. These interventions can help reduce LST and improve the overall livability of the city.

Future research should focus on integrating high-resolution data sources and incorporating socio-economic factors to provide a more detailed analysis of the drivers of urban growth and temperature increases. Interdisciplinary approaches, combining urban planning with climate science, are essential for developing comprehensive strategies to manage the environmental impacts of urbanization. Additionally, adapting this research approach to other regional contexts, considering local climate, infrastructure, and socio-economic conditions, will further enhance our understanding of urban climate dynamics.

This study offers critical insights into the links between urbanization and local climate change in Patna, providing a foundation for more effective urban planning and environmental management practices. By addressing these challenges through both technical and policy interventions, cities like Patna can move toward more sustainable and resilient urban futures.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

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