ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-5/W2-2025
Unleashing the power of Geospatial & Frontier Technologies for a Sustainable Future – GIFTS Summit 2025,
1–3 September 2025, Symbiosis International University, Pune, India

A Geospatial Framework for Assessing Urban Environmental Criticality: A Case of Kidderpore, Kolkata

Swadhina Koley and Mohit Kumar

Department of Geography, School of Basic & Applied Sciences,
Adamas University, Barasat, Kolkata – 700126, India

Corresponding author email: swadhina.koley1@adamasuniversity.ac.in

Keywords: NDVI; NDBI; LST; ECI; Urban planning.

Abstract

Urbanization has emerged as a dominant driver of environmental transformation, leading to increased surface temperatures, loss of vegetation, and pressure on infrastructure systems. This kind of rapid transformation often leads to environmental degradation, thus impacting livelihood. This research aims to quantify the impact of rapid urban growth on the environment through the Environmental Criticality Index (ECI) derived from Landsat 8 datasets. The Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Land Surface Temperature (LST) were calculated over the Kidderpore area in Kolkata metropolitan city in 2014, 2019, and 2024. The NDVI, NDBI, and LST were used to estimate the ECI in the above-mentioned periods. The calculated ECI was categorized into five classes: Very low, low, moderate, high, and very high. The results revealed that the area under very low ECI was 2.39 sq. km. in 2014, 1.88 sq. km. in 2019, and 1.51 sq. km. in 2024. The area under very high criticality was observed to be 3.84 sq. km. in 2014, 4.24 sq. km. in 2019, and 4.38 sq. km. in 2024. In the very highly critical areas, the mean LST in 2014 was observed to be 43.61°C. The mean LST in such areas increased to 45.69°C in 2019 and to 47.51°C in 2024. The mean NDBI values in very highly critical areas varied from -0.24 to 0.20 in 2014, -0.22 to 0.29 in 2019, and -0.17 to 0.38 in 2024. The research would help with sustainable urban planning through environmental risk monitoring.

1. Introduction

India is experiencing rapid vertical and horizontal urbanization to fulfill the needs of a growing population. India boasts the second-largest urban system worldwide, housing around 11% of the global urban population (Mandvikar et al., 2024). This demand has brought about overwhelming alterations in land use and land cover (LULC), especially in urban areas. In numerous urban environments, the impacts of transformation are pronounced. There is a notable decrease in green spaces, an expansion of impervious surfaces such as concrete and asphalt, and a rise in land surface temperatures (Pal and Ziaul, 2017; Ranagalage et al., 2017). These alterations significantly contribute to the phenomenon of urban environmental degradation, posing serious challenges to sustainability and urban resilience. So, urban centers, particularly those with dense populations, experience extreme heat discomfort, elevated pollution levels, and higher consumption of energy. This elevated heat not only poses severe threats to public health, exacerbating conditions such as heat exhaustion and cardiovascular issues, but also places substantial strain on infrastructure, increasing energy demand for cooling, and elevating the risk of heat-related emergencies (Jabbar et al., 2023; Mourougan et al., 2024).

The alterations in land cover have significantly impacted the interaction between the land surface and the atmosphere. This changed dynamics not only results in the Urban Heat Island (UHI) effect (Grover and Singh, 2015), but also worsens the environmental condition. In recent years, several geospatial indices have been developed to monitor and evaluate urban environmental conditions. Environmental Criticality Index (ECI) is one of the widely used parameters to monitor such conditions. Environmental criticality refers to the degree to which an area is susceptible to ecological degradation due to anthropogenic pressures. It is often marked by factors such as reduced vegetation, poor air quality, increased surface temperature, and an overall decline in environmental livability.

Kolkata, one of India's most populous metropolitan cities, has witnessed rapid and often unplanned urban expansion over the last few decades. Kidderpore, with its colonial-era infrastructure and complex socio-economic profile, reflects the pressures of such expansion more acutely. It is not only historically significant but also environmentally sensitive due to its proximity to the Hooghly River and low-lying topography. The river suffers from industrial discharge, sewage incursion, and the oil spills from the port operations, which lead to significant water pollution in this region. Besides, vehicular emissions and industrial exhaust contribute to poor air quality, affecting public health. Moreover, encroachments of wetlands and green spaces for housing and infrastructure reduce natural buffers against flooding. Such issues make the region more vulnerable to environmental criticality. Identifying areas within Kidderpore that are environmentally highly critical is essential for formulating targeted interventions such as urban greening, heat mitigation strategies, and infrastructure retrofitting.

Assessing such criticality is essential for identifying urban hotspots that require immediate planning and mitigation interventions. However, traditional field-based methods for such assessments are often time-consuming and spatially limited. Geospatial technologies, such as Geographic Information Systems (GIS) and remote sensing, are essential tools for mapping and analyzing built-up areas that help policymakers identify high-risk areas (Bhatti and Tripathi, 2014). Technologies like satellite imagery and aerial monitoring are invaluable for observing thermal variations. By capturing comprehensive data on land surface temperatures and the distribution of heat within urban areas, these technologies empower urban planners and policymakers with important insights into the thermal dynamics at play. Thermal indices can be useful to measure the ECI index. Land Surface Temperature estimated through remote sensing data, along with other spectral indices, was used to estimate the ECI (Mallik et al., 2023; Saputra et al., 2023; Sasmito and Suprayogi, 2018).

The Normalized Difference Vegetation Index (NDVI) is one of the indicators that provides crucial information about the overall vegetation condition over a region. On the other hand, the Normalized Difference Built-up Index (NDBI) is useful to extract the built-up intensity. Another critical indicator in this context is the Land Surface Temperature (LST), which reflects the thermal state of the Earth's surface and is closely tied to the urban heat island (UHI) effect. Hence, NDVI and NDBI, when integrated with the LST, can provide quantitative information on the environmental criticality.

The present study seeks to address this issue by developing a geospatial framework using the NDVI, NDBI, and LST to assess urban environmental criticality, with Kidderpore as a case study. A standardized methodology has been adopted, allowing for meaningful comparisons across multiple temporal snapshots. The study also aims to explore the spatiotemporal pattern of NDVI, NDBI, and the LST over a decadal period from 2014-2024. The findings aim to guide local urban planning bodies, policymakers, and sustainability practitioners in making informed, data-driven decisions to bolster environmental resilience in vulnerable urban areas.

2. Study area, materials, and methods

2.1 Study area

The study area, Kidderpore, is located in the western part of the Kolkata district in West Bengal, lying along the eastern bank of the Hooghly River. It falls under the Kolkata Municipal Jurisdiction, consisting of the ward numbers 76 and 77. The area is located at about 22.53° N and 88.32° E. The spatial extent covered by these two wards is about 0.9 sq. km. The area is known for its dense and mixed urban settlements comprising residential, commercial, and port-related activities. The area is home to the Kidderpore Dock, part of the Syama Prasad Mookerjee Port (formerly known as the Kolkata Port Trust). This makes it an important hub for maritime trade and transportation. Additionally, the region features a blend of low-income settlements, historical buildings, and modern infrastructure, showcasing its urban diversity. In this study, a buffer of 2km was applied around the two wards. However, since the buffer area crosses on the other side of the Hooghly River, that is outside the Kolkata Municipality, only the area (about 17 sq. km.) on the eastern bank of the river was considered for this study. Figure 1 represents the geographical location of the study area.

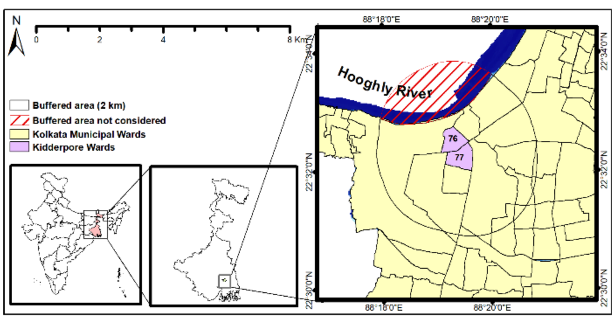

Figure 1. Location of the study area

2.2 Materials

Landsat 8 data from 2014, 2019, and 2024, obtained from the United States Geological Survey (USGS) Earth Explorer portal (https://earthexplorer.usgs.gov/), were used for this research. The Optical Land Imager (OLI) of the Landsat 8 provides nine spectral bands with wavelengths ranging from 0.43 – 1.38 µm at a spatial resolution of 30m, and the Thermal Infrared Sensor (TIRS) provides two thermal bands with wavelengths ranging from 10.6 – 12.51 µm at a spatial resolution of 100m (resampled to 30m). For this study, the red band (0.64 – 0.67 µm), the near infrared band (0.85 – 0.88 µm), the short-wave infrared 1 band (1.57 – 1.65 µm) for generating the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Buil-up Index (NDBI). However, the Land Surface Temperature (LST) was directly acquired from the Band 10-derived (10.6 - 11.19 µm) surface temperature band. Details of the satellite images used are mentioned in Table 1.

Scene Id	Date of acquisition	File format
LC81380442014128LGN01	8th May 2014	GeoTiff
LC81380442019126LGN00	6th May 2019	GeoTiff
LC81380442024124LGN00	3rd May 2024	GeoTiff

Table 1: Details of the satellite images

2.3 Methods

The research uses two spectral indices, i.e., NDVI and NDBI, along with the LST to calculate the ECI. The NDVI, proposed by Rouse et al. (1974), is a proxy for the vegetation vigor. The value of NDVI varies from -1 to +1. A value close to 1 indicates the presence of denser and healthier vegetation, whereas lower values (near 0 or less than 0) represent minimum or no vegetation cover. The NDVI was calculated using the following equation:

$$NDVI = \frac{NIR-Red}{NIR+Red} \tag{1}$$

The NDBI was first proposed by Zha et al. (2003)to extract the impervious features on the land surface. This index enhances built-up features by exploiting the higher reflectance of urban surfaces in the SWIR region compared to the NIR. Similar to the NDVI, NDBI also varies from -1 to +1. Higher NDBI values typically correspond to dense built-up or impervious areas. The following formula was used to create the NDBI image using the Landsat 8 OLI data:

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \tag{2}$$

Though the LST was directly obtained from the level 2 datasets of the Landsat 8 TIRS sensor, the algorithm behind the estimation of the LST using the Landsat thermal bands is mentioned below.

1) Estimating the fractional vegetation cover

In LST retrieval, surface emissivity significantly influences the accuracy of thermal infrared-derived temperatures. Since vegetated surfaces and bare soil have different emissivity values, the fractional vegetation cover (FVC) is used to estimate a pixel-wise emissivity by linearly combining the emissivities of pure vegetation and bare soil. The FVC is defined as the proportion of ground surface covered by vegetation within a pixel, and is calculated using the following equation:

$$P_v = \left(\frac{NDVI-NDVI_{min}}{NDVI_{max}-NDVI_{min}}\right)^2 \tag{3}$$

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Where P_v is the fractional vegetation cover, $NDVI_{min}$ and $NDVI_{max}$ are the minimum and Maximum NDVI values obtained.

2) Calculating Land Surface Emissivity (LSE)

The LSE is estimated using the following equation:

$$LSE = (0.004 \times P_v) + 0.986 \quad (4)$$

3) Calculating LST

To calculate the LST, first the brightness temperature (BT) is estimated using the top-of-atmosphere (TOA) spectral radiance and the calibration constants of the thermal band. The TOA spectral radiance is calculated using the following formula:

$$L_\lambda = M_L Q_{Cal} + A_L \quad (5)$$

Where L_λ is the spectral radiance at a particular wavelength λ, M_L and A_L are the multiplicative and additive factors corresponding to the specific thermal band, and Q_{Cal} is the quantized pixel value.

The BT is then calculated using Eq. 6 as mentioned below:

$$T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda}+1\right)} - 273.15 \quad (6)$$

K_1 and K_2 are the calibration constants having values 774.89 and 1321.08, respectively, for Landsat 8 Band 10. After the brightness temperature has been calculated, it is then converted to the LST values using Eq. 7:

$$LST = \frac{BT}{\left(1+\lambda \times \frac{BT}{1.4388}\right)} \times \ln(LSE) \quad (7)$$

The Landsat 8 Band 10 provides the LST values in Kelvin (K) in a scaled range of 0 to 65535. A scaling factor of 0.00341802 and an offset value of 149 were applied to extract the actual surface temperature.

Next, the built-up index (BU) was calculated by taking the difference between the NDBI and NDVI (Eq. 8).

$$BU = NDBI - NDVI \quad (8)$$

Finally, the ECI was calculated using the following equation:

$$ECI = LST \times BU \quad (9)$$

The detailed methodology of the workflow is represented by Figure 2.

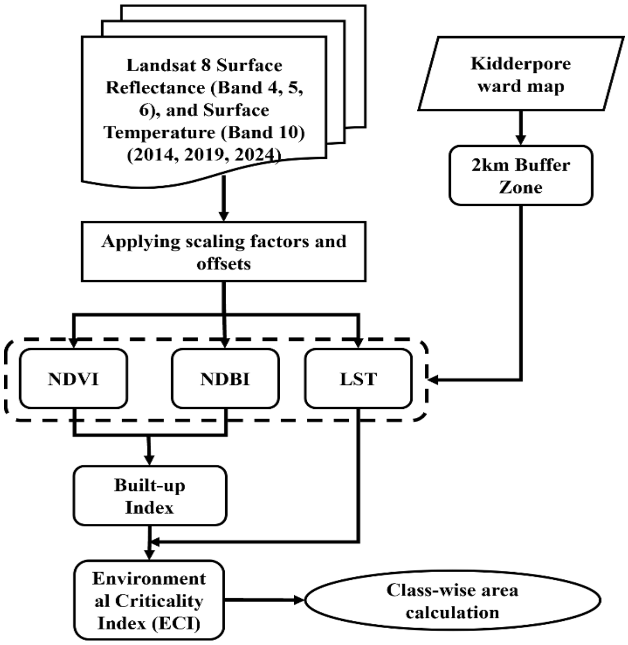

Figure 2. Methodology of the work

3. Results and Discussions

3.1 Results

3.1.1 Assessment of NDVI and NDBI: The results revealed that the NDVI varied from -0.19 to 0.83 in 2014, -0.03 to 0.76 in 2019, and -0.08 to 0.75 in 2024. The mean NDVI was observed to gradually decrease from 2014 to 2024, indicating a possible degradation of vegetation health over the years. The statistical values of the obtained NDVI in three different years have been shown in Table 2. The spatial distributions of the NDVI over the study area in 2014, 2019, and 2024 are shown in Figure 3.

Year	Minimum	Maximum	Mean	Std. Dev
2014	-0.19	0.83	0.38	0.14
2019	-0.03	0.76	0.37	0.16
2024	-0.08	0.75	0.31	0.12

Table 2: NDVI values obtained at three different times

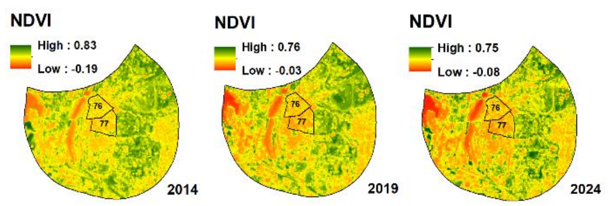

Figure 3. Spatial distribution of NDVI in three years

The NDBI varied from -0.48 to 0.29 in 2014, -0.43 to 0.30 in 2019, and -0.44 to 0.38 in 2024. The mean NDBI value increased from 0.08 to 0.14 over the ten years. Table 3 shows the statistical values obtained for the NDBI in the three years. Figure 4 represents the spatial distributions of the NDBI in the said periods.

Year	Minimum	Maximum	Mean	Std. Dev
2014	-0.48	0.29	0.08	0.10
2019	-0.43	0.30	0.10	0.10
2024	-0.44	0.38	0.14	0.08

Table 3: NDBI values obtained at three different times

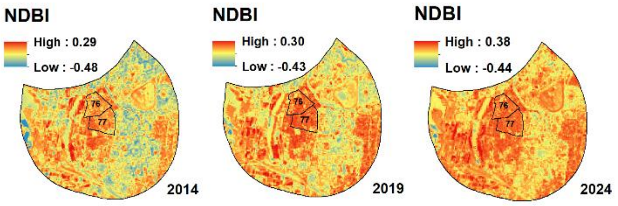

Figure 4. Spatial distribution of NDBI in three years

3.1.2 Assessment of LST: The Land Surface Temperature (LST) values show a clear upward trend over the decade, with the mean LST rising from 42.40°C in 2014 to 46.38°C in 2024, and the maximum LST reaching as high as 55.06°C in 2024 (Table 4). This consistent increase in both mean and maximum LST indicates intensifying surface heating over the study area. Figure 5 shows the spatial distribution of LST over the study area in 2014, 2019, and 2024.

Year	Minimum	Maximum	Mean	Std. Dev
2014	33.98	52.09	42.40	2.84
2019	33.37	53.20	44.72	2.78
2024	34.25	55.06	46.38	3.08

Table 4: LST values obtained at three different times

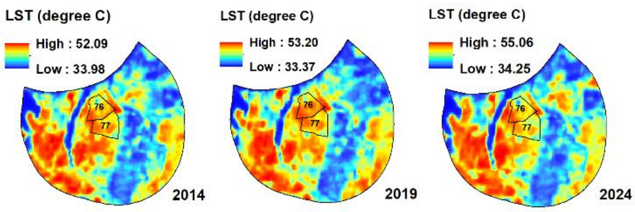

Figure 5. Spatial distribution of LST in three years.

When observed in relation to the NDVI and NDBI patterns, the rising LST trend appears closely linked to changes in land cover characteristics. The gradual decline in vegetation cover over the years suggests a weakening of natural cooling processes like evapotranspiration. At the same time, the steady increase in built-up areas points to greater surface sealing, which tends to trap and radiate more heat. Together, these shifts reflect how urbanization and vegetation loss have likely contributed to the intensifying surface temperatures in the region.

3.1.3 Relationship between LST, NDVI, and Built-up index: The relationship between the vegetation coverage, the built-up index and the LST has been analysed through the correlation obtained between these parameters. It was observed that the areas with higher vegetation coverage experience comparatively lower surface temperature than the areas with less vegetation cover. Hence, the NDVI showed a negative correlation with the LST with R = -0.57, -0.63, and -0.64 in 2014, 2019, and 2024, respectively (refer to Figure 6). Conversely, the built-up index showed a positive correlation with the surface temperature with R = 0.65, 0.66, and 0.79, in 2014, 2019, and 2024, respectively (refer to Figure 7). These findings suggest an intensifying urban heat island effect over the years, with built-up expansion exerting a stronger influence on surface temperature. The increasing correlation values highlight how urbanization has progressively amplified thermal stress in the region.

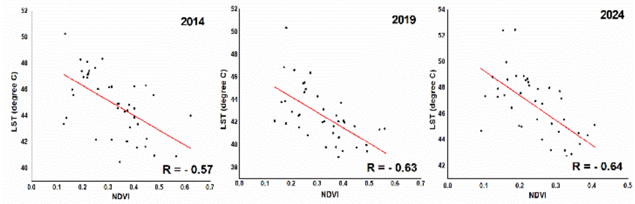

Figure 6. Correlation between NDVI and LST.

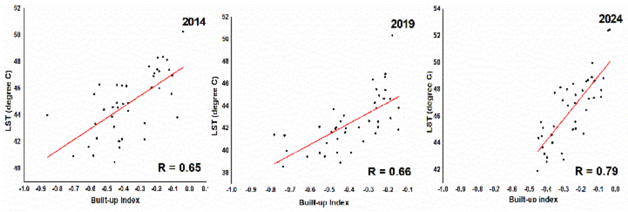

Figure 7. Correlation between BU and LST

3.1.4 Analysis of the ECI: In this study, the Environmental Criticality Index (ECI) has been measured using the built-up index (BU) and the land surface temperature (LST). The spatial distribution of the ECI is shown in Figure 8. The ECI was categorized into five classes: very high criticality, high criticality, moderate criticality, low criticality, and very low criticality. The ECI was observed to gradually increase over the years. The spatial pattern of the ECI revealed that the area under very low ECI was 2.39 sq. km. in 2014, 1.88 sq. km. in 2019, and 1.51 sq. km. in 2024. The area under very high criticality was observed to be 3.84 sq. km. in 2014, 4.24 sq. km. in 2019, and 4.38 sq. km. in 2014. The built-up index and the LST showed a significantly positive correlation with the ECI. The correlation between the BU, LST, and ECI for the year 2024 is represented by Figure 9. In the very highly critical zones, the mean LST was 43.61 °C in 2014, which rose to 45.69 °C in 2019 and further increased to 47.51 °C by 2024. The steady rise in mean LST within very highly critical areas indicates a progressive intensification of heat over the decade. This trend points to worsening thermal conditions, likely linked to increasing environmental stress and land surface changes.

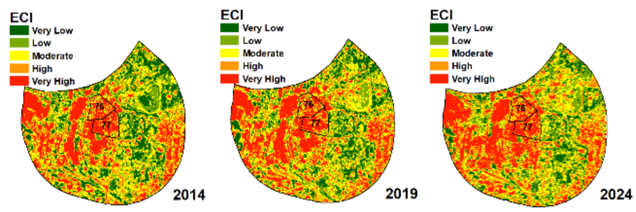

Figure 8. Spatial distribution of ECI in three years

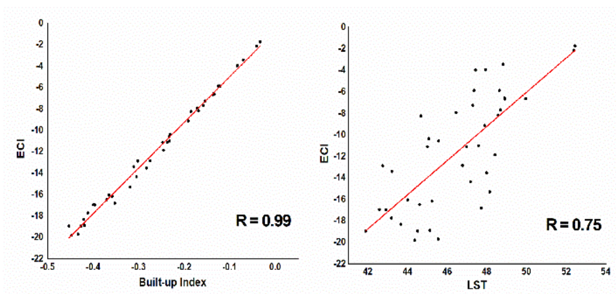

Figure 9: Correlation between Built-up Index, LST, and ECI for the year 2024

3.2 Discussion

The analysis of NDVI, NDBI, and LST over the period from 2014 to 2024 reveals a clear transformation in the surface characteristics of the study area and highlights the implications of urbanization on the local thermal environment. The NDVI results demonstrate a gradual decline in mean vegetation index values, from 0.38 in 2014 to 0.31 in 2024, accompanied by a reduction in maximum NDVI. This indicates a progressive deterioration of vegetative cover and possibly a reduction in overall vegetation health. In contrast, the NDBI exhibits an upward trend, with the mean values increasing from 0.08 in 2014 to 0.14 in 2024. This pattern signifies an expansion of impervious or built-up surfaces, which is consistent with ongoing urban growth.

The rising trend in LST corresponds closely with these land cover changes. The mean LST has increased from 42.40 °C in 2014 to 46.38 °C in 2024, while the maximum LST reached 55.06 °C in 2024. Such increases reflect a strong relationship between surface composition and thermal behavior. As vegetated areas decline, their cooling effect through shading and evapotranspiration is diminished, whereas the proliferation of built-up areas contributes to heat retention due to materials with low albedo and high heat capacity.

These findings highlight the synergistic effects of vegetation loss and urban expansion on thermal conditions, leading to the intensification of the urban heat island effect. If these trends continue, they may exacerbate environmental stress, energy demand, and thermal discomfort in the region. Urban planning measures such as enhancing green cover, integrating green infrastructure, and adopting reflective building materials are essential to mitigate these adverse effects (Bowler et al., 2010). Also, high-albedo materials can be used through cool roofs and pavements to reflect more solar radiation, reducing surface temperature and cooling demands (Santamouris, 2014). This study underscores the importance of using geospatial indices and thermal data to monitor land surface changes and their implications for sustainable urban development. The geospatial framework adopted in this study can be scaled to other urban areas experiencing similar environmental transitions.

3.3 Conclusion

This research aims to demonstrate the land cover dynamics in the highly dense Kidderpore urban area and the effect of urban sprawl on the environmental condition. The decadal analysis at a five-yearly interval clearly depicted the inter-relationship between the degraded vegetation health, increasing built-up areas, and the environmental criticality. The decreasing NDVI values clearly indicate a decline in vegetative cover, while the steadily rising NDBI reflects the expansion of impervious and built-up surfaces. Land cover changes have significantly increased land surface temperature, with an average rise of nearly 4°C over the past decade. This further resulted in the gradual increase in environmental criticality. The increase in the area under very high criticality confirms the need for the establishment of sustainable urban development. These findings highlight the urgent necessity of integrating land cover management and greening strategies into urban development policies. The outcomes of this research would be beneficial for local government and urban planners for such strategic planning to ensure relief from issues like heat stress through the enhancement of green spaces, leading to sustainable urban development.

Acknowledgements

The authors also convey their gratitude to the National Aeronautics and Space Administration (NASA) for freely providing the satellite imagery required for this research.

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