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The Effects of Vegetation & Bare Land on Thermal Characteristics: A Case Study of Three Indian Metropolitan Areas

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ABSTRACT

Urban expansion in India's metropolitan regions has led to significant alterations in land surface composition, which directly affect local thermal environments. Vegetation loss and the emergence of bare land surfaces are increasingly recognized as key contributors to urban heat, yet comparative, multi-city studies addressing their combined effects remain scarce. This study analyzes the influence of vegetation and bare land on land surface temperature (LST) across three major Indian cities—Delhi, Lucknow, and Ahmedabad in 2023. Satellite imagery was used to extract Normalized Difference Vegetation Index (NDVI), Normalized Difference Bareness Index (NDBaI), and LST values. Statistical correlation and spatial analysis techniques were applied to evaluate thermal variations across land cover types. NDVI was negatively correlated with LST ($r = -0.68$ to -0.81), indicating the cooling role of vegetation, whereas NDBaI showed a positive correlation with LST ($r = 0.59$ to 0.74), highlighting the warming effect of bare surfaces. Delhi exhibited the highest maximum LST (47.45 °C), while Lucknow recorded the highest minimum (38.63 °C). Across all cities and timeframes, vegetated areas consistently showed lower surface temperatures compared to bare or built-up regions. The findings emphasize the importance of vegetation in reducing urban heat and the thermal risk posed by increasing bare land. Strengthening green infrastructure and minimizing exposed soil in urban areas can serve as effective strategies for enhancing thermal comfort and climate resilience in Indian cities.

Keywords: Vegetation; Urban Heat; Indices; Microclimate; Bare Land

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1. Introduction

Urban sustainability has become a central tenet of contemporary city planning as cities confront intensifying environmental pressures worldwide. Rapid urbanisation—characterised by expansive construction, densifying populations, and ecological fragmentation—has triggered numerous environmental and social challenges. These include increased waste generation [1], worsening air [2] and water pollution [3], and, most critically, the intensification of surface thermal stress within urban environments [4, 5]. Among these, the Urban Heat Island (UHI) effect—where urban areas exhibit significantly higher surface temperatures than adjacent vegetated or rural zones—has emerged as a particularly urgent concern [6, 7]. It affects urban resilience [8], environmental quality [9], and public health [9,10], contributing to heat-related illnesses [11], increased cooling energy demands [12], and socio-economic stress [13], especially among vulnerable populations with limited adaptive capacity.

The spread of impervious surfaces primarily drives this intensification of urban surface temperatures, the decline of vegetation, and the expansion of exposed bare land. Vegetation plays a crucial role in moderating thermal conditions through shading and evapotranspiration, all of which contribute to cooling effects and microclimatic stability [14, 15]. Whereas, bare land—lacking vegetative cover and often comprising exposed soil or degraded ground—exhibits high thermal absorption and low reflectivity, resulting in substantial heat accumulation [16–18]. The thermal contrast between these surface types becomes especially pronounced in compact, high-density urban centres where natural land cover is increasingly scarce [17, 18]. Microclimatic variation across urban settings—driven by heterogeneity in land surface characteristics—is central to understanding the uneven impacts of heat [19, 20]. Interactions among vegetative cover, built-up structures, and bare surfaces produce highly variable thermal landscapes, with distinct intra-urban disparities in heat accumulation and dissipation [19–21]. The absence or reduction of vegetation, particularly in rapidly urbanising or peri-urban zones, weakens ecological regulation and intensifies thermal loading [21, 22]. This exacerbates public exposure to extreme heat, raising concerns not only about environmental sustainability but also about social justice and urban equity [22–25].

While global studies have increasingly examined these dynamics using remote sensing techniques, research in the Indian context remains limited, especially in terms of comprehensive assessments that distinguish bare land as a thermally significant surface category. Existing Indian and international studies often simplify land surface classifications into a built-up versus green dichotomy, thus failing to acknowledge bare land as an independent, heat-contributing land type [14–16, 26–28]. This binary framing obscures the role of bare land, which is particularly prevalent in transitional zones and peri-urban landscapes that undergo rapid land use conversion. Additionally, many earlier works lack cross-city comparisons, focus narrowly on single urban case studies, or do not incorporate spatiotemporal variation in surface characteristics, limiting the generalisability and depth of thermal impact assessments [29–32].

To address these limitations, the present study undertakes a spatially explicit, cross-city analysis of the thermal effects of vegetation and bare land in three ecologically and demographically distinct Indian cities: Delhi, Lucknow, and Ahmedabad. These cities, situated in different climatic zones and urban typologies, offer a comparative lens through which to assess the role of surface composition in shaping urban thermal behaviour. Using satellite-derived data and geospatial indices such as NDVI, NDBaI, and the Urban Thermal Field Variance Index (UTFVI), the study investigates how vegetation and bare land influence localised heat intensity and thermal variability. The research specifically aims to examine spatial temperature variation, quantify and map vegetation and bare land distribution, and evaluate surface composition's influence on thermal stress across diverse urban environments. The following are the specific objectives of this study:

- To analyse the spatial variability of surface temperatures in Delhi, Lucknow, and Ahmedabad, identifying urban heat patterns.
- To map and assess vegetation and bare land distribution using NDVI and NDBaI across different periods.
- To evaluate the impact of surface composition on local thermal conditions using UTFVI.
- To derive comparative insights on how vegetation and bare land influence urban heat across varied climatic settings.

By integrating high-resolution thermal metrics with geospatial indicators, this study contributes to urban climate resilience discourse and calls for a rethinking of urban landscape planning in India. It argues for a move beyond the traditional green–built-up dichotomy and highlights the critical, yet often overlooked, thermal role of bare land in shaping urban heat dynamics. The novelty of this research lies in its cross-city, spatiotemporal approach that systematically distinguishes and quantifies the effects of both vegetation and bare land on thermal variation. These findings are expected to inform evidence-based urban planning and policymaking focused on heat mitigation, ecological restoration, and equitable development in rapidly transforming Indian cities.

2. Materials and Methods

2.1. Study Area

This study provides a comparative spatial analysis of three major Indian metropolitan cities—Delhi, Lucknow, and Ahmedabad—representing the Northern, Central-Gangetic, and Western regions of the country, respectively (**Figure 1**). These cities were selected not only for their contrasting geographic and climatic characteristics but also for their representativeness in terms of diverse urban morphologies, thermal profiles, and land cover dynamics. Collectively, they provide a cross-sectional understanding of urban heat patterns and land surface transformations across different ecological and developmental contexts in India.

Delhi, the national capital and core of the National Capital Region (NCR), spans approximately 1,483 km² with a population exceeding 16.7 million (Census, 2011). The city experiences a composite climate and topographical diversity shaped by the Delhi Ridge and Yamuna River. In recent decades, Delhi has faced extensive urban transformation, with the proliferation of impervious surfaces, decline in vegetation, and expansion of informal settlements contributing to intense urban heat stress, elevated cooling energy demand, and growing discomfort in densely populated zones.

According to the district website, Lucknow, the capital of Uttar Pradesh, located in the Middle Gangetic Plains, is traversed by the Gomti River. With a population of around 4.6 million and an average elevation of 123 meters, it features a humid subtropical climate. The city's rapid outward growth, driven by migration and economic liberalization, has led to encroachment on natural vegetation and open lands, triggering significant microclimatic imbalances, particularly increased surface temperatures and reduced thermal comfort in peripheral areas.

Ahmedabad, Gujarat's largest city, is situated on the Sabarmati River and spans around 464 km² with a population of over 5.5 million. Characterized by a semi-arid climate and low-lying topography, the city is highly vulnerable to extreme heat conditions. The expansion of built-up areas and limited vegetation cover has resulted in heightened urban heat island effects, necessitating increased energy use for cooling and compounding the city's vulnerability to climate-induced heat stress. In recent decades, Ahmedabad has become a central hub for commerce, industry, and education. The peri-urban areas of the city are rapidly urbanizing, with notable portions of agricultural and fallow land being repurposed for residential and industrial uses. By selecting these three cities, the study aims to capture regional thermal disparities and assess the interplay of vegetation and bare land in influencing local heat conditions under varying climatic regimes and development pressures.

The comparative analysis of these three cities is presented in **Table 1**. The selection of Delhi, Lucknow, and Ahmedabad as study subjects is informed by their varying climatic conditions, unique urban forms, and significant patterns of environmental change. These cities offer a valuable framework for understanding the spatial dynamics of urban heat under differing geographical and climatic influences. As a densely populated metropolis, Delhi faces substantial infrastructure-induced thermal stress, particularly influenced by the Delhi Ridge and Yamuna floodplain. Lucknow demonstrates moderate urban growth while increasingly facing challenges from horizontal sprawl over vegetated and riverine areas. As a semi-arid city, Ahmedabad rapidly converted its peripheries into residential and industrial zones, altering its thermal conditions. Including these diverse urban environments enables a thorough analysis of urban thermal behaviour and land cover changes across ecologically and climatically varied contexts.

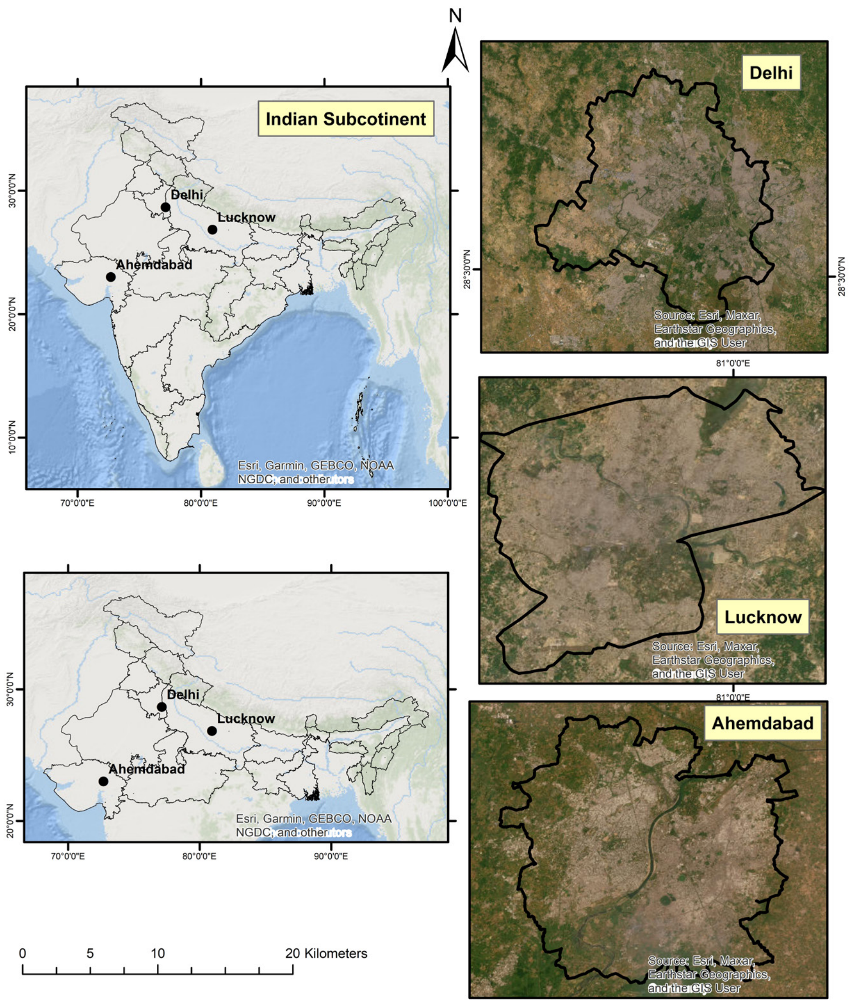

Figure 1. Study Area Location Map.

Table 1. Comparative Analysis of the Cities.

Parameter	Delhi	Lucknow	Ahmedabad	Source
Location	Northern India	Central-Gangetic Plains	Western India	Survey of India (https://surveyofindia.gov.in/)
Average Elevation (m AMSL)	216 m	123 m	50 m	Survey of India (https://surveyofindia.gov.in/)
Area (km²)	1,483	631	464	Survey of India (https://surveyofindia.gov.in/)
Population (2011 Census)	16.7 million	4.6 million	5.5 million	Census of India (https://censusindia.gov.in/census.website/)
Mean Annual Temperature Range (°C)	Max: 20.1–39.9 °C Min: 27.7–7.5 °C	Max: 19.5–39.2 °C Min: 26.9–7.0 °C	Max:21.3–42.4 °C Min: 28.0–9.5 °C	Indian Meteorological Department (https://mausam.imd.gov.in/)
Highest Recorded Temperature (°C)	49.1 °C (Najafgarh, May 2024)	45.7 °C (May 1998)	48.0 °C (May 2016)	Indian Meteorological Department (https://mausam.imd.gov.in/)
Lowest Recorded Temperature (°C)	3.9 °C (Safdarjung, December 2020)	0.7 °C (January 1945)	5.0 °C (January 1935)	Indian Meteorological Department (https://mausam.imd.gov.in/)
Annual Average Rainfall (mm)	692 mm	917.3 mm	782 mm	Indian Meteorological Department (https://mausam.imd.gov.in/)
Key Water Body	Yamuna River	Gomti River	Sabarmati River	Google Earth (https://earth.google.com/web)

2.2. Data Sources

Remote sensing techniques have been widely employed in recent studies to analyze urban thermal characteristics and land surface temperature (LST) dynamics across diverse urban environments. Bagyaraj et al. conducted a spatiotemporal analysis in Kancheepuram, Tamil Nadu, utilizing Landsat imagery to assess changes in LST, NDVI, and LULC, revealing a 152% increase in mean LST over four decades due to rapid urbanization, sparse vegetation, and impervious surfaces [33]. Cafaro et al. proposed a GIS-based framework using the ISODATA clustering algorithm and satellite-derived LST data to detect thermally critical hotspots in Naples, Italy, demonstrating the influence of vegetation cover and permeable open spaces in moderating elevated surface temperatures during extreme events [34]. Similarly, Jumari et al. applied thermal remote sensing in Kuala Lumpur, Malaysia, showing how increased urban development and vegetation loss correlate with intensified surface heating, with temperature differences between urban and rural areas reaching up to 26.73 °C [35]. These studies validate the use of thermal and vegetation indices derived from satellite data in capturing spatial and temporal thermal variations, supporting the methodological foundation of this study to examine vegetation, barren land, and land surface interactions in Indian metropolitan cities.

The present study relied on remotely sensed geospatial datasets acquired from reputable open-access satellite data platforms—USGS Earth Explorer and NASA Earth Data—to evaluate the relationship between vegetation, bare land, and Land Surface characteristics intensity across the cities of Delhi, Lucknow, and Ahmedabad (**Table 2**). Two major satellite systems were employed: Landsat 8 (Operational Land Imager [OLI] and Thermal Infrared Sensor [TIRS]) and MODIS Terra. Landsat 8 data, with a spatial resolution of 30 meters for reflective bands and 100 meters (resampled to 30 meters) for thermal bands, provided medium-resolution observations suitable for urban-scale analysis of land surface characteristics [36–41]. With its 1-kilometre resolution, the MODIS Terra sensor offered complementary thermal data with higher temporal frequency, enabling temporal consistency and cross-validation of land surface temperature (LST) [42, 43]. Landsat Level 2 Surface Reflectance and Surface Temperature products were utilised due to their atmospheric correction and ready-to-use format, ensuring radiometric consistency across study sites. Each image was clipped to the municipal administrative boundaries of the respective study areas using official vector shapefiles obtained from the Survey of India, facilitating spatial specificity and minimizing edge effects during analysis.

Table 2. Datasets used

Satellite	Spatial Resolution	Bands	Sensor	Time	Cloud Cover	Source
Landsat 8	30 m	4,5,6,10	OLI & TIRS	June 2023	Less than 30%	USGS Earth Explorer
MODIS	1 km	-	Terra	June 2023	Less than 30%	NASA Earth Data

2.3. Methods

2.3.1. LST Estimation

Land Surface Temperature

Land Surface Temperature (LST) was estimated using data from the MODIS Terra sensor, which offers reliable thermal infrared observations for surface temperature assessment. The digital numbers (DN) retrieved from MODIS LST products were converted into degrees Celsius using the standard radiometric calibration equation:

$$\mathrm{LST}(°\mathrm{C}) = DN * 0.02 - 273.15 \tag{1}$$

This transformation, where DN represents the scaled digital number derived from the MODIS thermal band, enabled consistent and spatially explicit LST value extraction across the selected urban regions. Despite its coarser spatial resolution (1 km), MODIS data were instrumental due to their high temporal resolution, facilitating robust cross-city comparisons of urban heat characteristics.

Urban Thermal Field Variance Index

The Urban Thermal Field Variance Index (UTFVI) was computed to quantify spatial disparities in surface temperature and identify thermal stress zones. UTFVI is a diagnostic metric that reflects the deviation of localized LST values from the urban mean, thereby providing a proxy for surface heat stress intensity. It is defined as:

$$UTFVI = 1 - \frac{\mathrm{LSTMean}}{\mathrm{LSTPixel}} \quad (2)$$

Areas with higher UTFVI values are considered thermally stressed zones, often associated with bare land, sparse vegetation, and dense built-up features. UTFVI values were calculated using MODIS-derived LST in a GIS environment, facilitating spatial delineation of heat-impacted zones [44-47].

2.3.2. Land Surface Feature Characterization Using Spectral Indices

To assess the contribution of different land cover types—particularly vegetation and bare soil—to LST variability, several spectral indices were derived from Landsat 8 OLI imagery. These indices enabled detailed mapping of land surface features at a spatial resolution suitable for urban-scale investigations.

Normalised Difference Vegetation Index (NDVI)

NDVI was calculated to evaluate vegetation distribution and health across the study areas. Numerous studies have demonstrated the crucial role of vegetation in influencing urban thermal characteristics. Liu et al. [48] found that green spaces in Beijing, despite occupying only about 30% of the study area, effectively reduced the average land surface temperature (LST) by 1.32 °C. The spatial configuration, size, and complexity of green spaces significantly enhanced their cooling capacity and their influence on nearby communities. Schwaab et al.[49] further emphasized the contribution of urban trees in reducing LST across 293 European cities, reporting temperature differences of up to 8–12°C in Central Europe between tree-covered areas and built-up surfaces. Kirschner et al. [50] found that compact green spaces with dense tree cover in Prague reduced surrounding residential area LSTs by up to 2.3°C within a 400 m radius. In the context of tropical climates, Rizki et al. [51] observed that the greenest urban areas in East Jakarta, particularly those with urban forests, displayed the lowest LST values and the narrowest extent of heat-prone zones. Collectively, these studies support a strong inverse correlation between NDVI and LST, indicating that increasing NDVI values through vegetation enhancement leads to a measurable decrease in surface temperature, thereby improving the thermal comfort of urban environments. It is computed as:

$$\mathrm{NDVI} = \frac{\text{Near Infrared} - \text{Red}}{\text{Near Infrared} + \text{Red}} \quad (3)$$

where Band 5 (Near Infrared) and Band 4 (Red) correspond to Landsat 8 OLI bands, NDVI values close to +1 indicate healthy, dense vegetation. In contrast, values approaching zero or negative reflect built-up or barren surfaces [52–55].

Normalised Difference Bareness Index (NDBaI)

The NDBaI was utilised to delineate exposed soil and bare land surfaces, which are typically associated with higher LST due to reduced evapotranspiration. The index is formulated as:

$$\mathrm{NDBal} = \frac{\text{Short wave Infrared} - \text{Thermal}}{\text{Short wave Infrared} + \text{Thermal}} \quad (4)$$

where Band 6 (Shortwave Infrared 1) and Band 10 (Thermal Infrared) are specific to Landsat 8 OLI and TIRS sensors, higher NDBaI values denote areas dominated by barren or non-vegetated land cover[56].

To facilitate spatial interpretation and categorical analysis of land surface metrics—including Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Normalized Difference Bareness Index (NDBaI), and Urban Thermal Field Variance Index (UTFVI)—thresholding techniques were applied using both manual histogram analysis and the Natural Breaks (Jenks) classification method. The manual histogram approach visually inspected pixel value distributions within the raster datasets. This method enabled the identification of data clusters, inflexion points, and outlier thresholds based on the natural frequency distribution of pixel values. Manual classification was particularly useful for delineating value ranges representing urban cores, vegetated regions, and bare land, ensuring that context-specific variations in surface characteristics across cities were preserved. The data analysis primarily relied on descriptive statistics derived from geospatial datasets. Visual interpretation and correlation between land surface features and land surface temperatures were conducted. Correlation analysis and Multiple linear regression analysis was conducted using

NDVI and NDBaI as independent variables to assess their influence on LST across Delhi, Lucknow, and Ahmedabad. While advanced statistical models such as machine learning were not applied due to limited data, they are recommended for future research with larger datasets. The Methodology flowchart has been depicted in **Figure 2**.

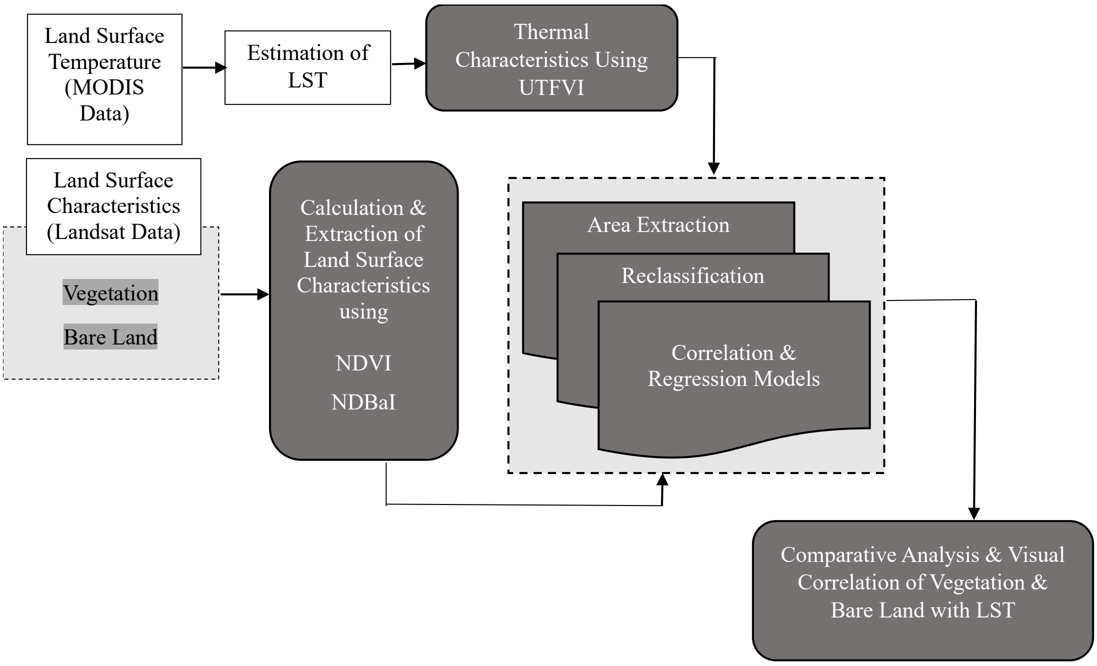

Figure 2. Methodology Flowchart.

3. Results

3.1. Results of NDVI Analysis

Vegetation analysis constitutes a vital component of thermal landscape studies, particularly in assessing the mitigating effects of green cover on urban surface temperatures. The Normalised Difference Vegetation Index (NDVI), derived from multispectral satellite imagery, quantifies vegetation density and health by assigning values within a standardised range of -1 to +1. Higher NDVI values generally indicate healthy and dense vegetation, such as forests, parks, and agricultural land. In contrast, values near 0 or negative represent non-vegetated surfaces, including built-up areas, barren lands, paved surfaces, or water bodies (**Figure 3**). This makes NDVI a powerful tool to assess land cover and ecological quality within urban regions.In the present study, spatial analysis of NDVI values revealed notable variability in vegetation density across the selected urban centres—Delhi, Ahmedabad, and Lucknow. The maximum NDVI values were recorded as 0.582 for Delhi, 0.543 for Ahmedabad, and 0.408 for Lucknow, suggesting relatively denser vegetation patches within Delhi and Ahmedabad than Lucknow. These values reflect localised ecological conditions and urban morphological structures that shape vegetation distribution (**Table 2**).

Area-wise statistical breakdown of high vegetation zones, defined by NDVI values, demonstrates significant inter-city contrasts (**Table 3**). Delhi exhibited the highest proportion of vegetated land, accounting for approximately 28.3% of its study area. Ahmedabad followed closely with 26.8%, while Lucknow registered a comparatively lower coverage of 21.2% (**Table 3**). These spatial patterns can be attributed to biophysical and anthropogenic factors, including topographic features, surface water availability, land-use practices, and infrastructural encroachment. The spatial clustering of higher NDVI values was particularly evident in proximity to major river systems—the Yamuna in Delhi, the Sabarmati in Ahmedabad, and the Gomti in Lucknow. These riparian corridors sustain higher vegetation levels due to improved soil moisture and microclimatic conditions. Conversely, urban cores and industrial zones, marked by impermeable surfaces and limited green infrastructure, showed suppressed NDVI signatures, underscoring the spatial disparity in vegetation cover across intra-urban landscapes.

3.2. Results of NDBaI Analysis

The Normalised Difference Bareness Index (NDBaI), a remote sensing-derived geospatial indicator, is instrumental in identifying and quantifying the spatial extent of bare and impermeable surfaces within urban and peri-urban landscapes (**Figure 3**). Functionally analogous to other biophysical indices, NDBaI leverages spectral reflectance patterns to distinguish barren terrain and anthropogenically altered surfaces from vegetated or natural covers. Values typically range between -1 and +1, with higher positive values signifying elevated degrees of surface exposure or soil imperviousness, while negative values generally denote vegetative or water-dominated areas.

In the context of this study, the spatial distribution of NDBaI across Delhi, Ahmedabad, and Lucknow reveals notable variations in surface bareness (**Figure 2**). Delhi exhibited the highest maximum NDBaI value at 0.4173, with a minimum of −0.6187, underscoring the significant presence of bare or constructed surfaces interspersed with vegetative patches. Ahmedabad recorded a maximum of 0.2631 and a minimum of −0.6473, reflecting substantial arid zones along its expanding urban fringes. Lucknow presented comparatively moderate values, with a maximum of 0.07986 and a minimum of −0.467, suggesting a more heterogeneous surface composition with a relatively lower proportion of barren expanses (**Table 3**). Spatial analysis further identified specific zones within each city with high surface bareness. In Lucknow, peri-urban sectors such as Ghaila, IIM Road, Dubagga, and Sarojini Nagar comprise approximately 17.3% of the city's total study area, exhibiting pronounced NDBaI values. These areas have experienced rapid infrastructural expansion and encroachment of natural landscapes, contributing to an increase in exposed soil and impervious land. Similarly, in Ahmedabad, peripheral regions in the southwest and northwest—particularly around Chandkheda and Sanand—are marked by elevated NDBaI values, accounting for nearly 12.1% of the city's total area. These locations correspond to zones of ongoing urban transformation, where agricultural land is increasingly converted to development-ready parcels.

In Delhi, bare and impermeable surfaces are notably concentrated in the peri-urban stretches to the northwest and west, encompassing localities such as Bawana, Bankoli, and Ladpur. These zones, characterised by extensive industrial sprawl and informal land use conversion, contribute to approximately 13.6% of Delhi's study area and represent critical hotspots of thermal accumulation due to their limited vegetative buffer and high surface exposure (**Table 4**).

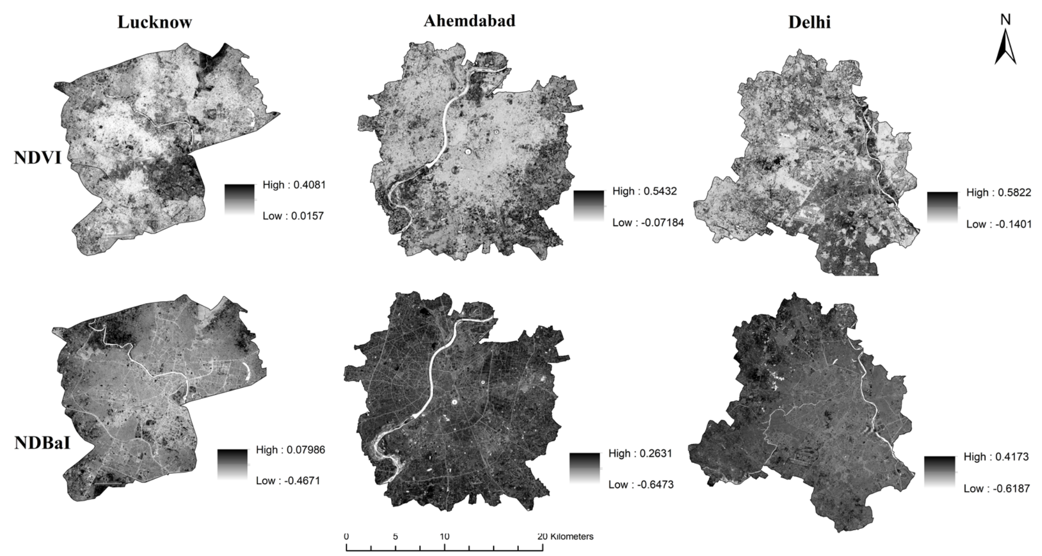

Figure 3. NDVI and NDBaI Mapping

Sources: Open Source Satellite Data(Landsat 8)

Table 3. Index Values

City	NDVI-Maximum	NDVI-Minimum	NDBaI-Maximum	NDBaI-Minimum
Lucknow	0.4081	−0.0157	0.07986	−0.4671
Ahmedabad	0.5432	−0.07184	0.2631	-0.6473
Delhi	0.5822	-0.1401	0.4173	−0.6187

Table 4. Area Statistics

City	High Vegetation Zones (per cent of total Area)	High Barren Land Zones (percent of total Area)
Lucknow	21.16	16.72
Ahmedabad	26.77	11.30
Delhi	28.29	12.14

3.3. Study of Thermal Characteristics

Land Surface Temperature (LST), a key indicator of the thermal state of the Earth's surface, is derived from satellite-based thermal infrared data. This study computed LST using MODIS thermal bands, wherein brightness temperature readings were calibrated and processed within a GIS environment to yield surface temperature estimates representative of June 2023 conditions (**Figure 4**).

The analysis of LST across the selected cities reveals pronounced intra-urban thermal disparities. Delhi exhibits the highest maximum LST at 47.45 °C and the lowest minimum at 35.13 °C, indicating the presence of both extreme thermal hotspots and cooler vegetated patches, leading to a substantial thermal amplitude of 12.32 °C. This wide range reflects heterogeneous land cover, with built-up clusters, bare lands, and scattered green zones contributing to localized microclimatic contrasts. Lucknow follows with a maximum temperature of 45.84 °C and a minimum of 38.63 °C, resulting in a narrower thermal range of 7.21 °C. This suggests a relatively uniform distribution of thermal features, with a moderate presence of vegetative buffers. Ahmedabad, by comparison, demonstrates a slightly lower maximum LST of 45.19 °C and a minimum of 37.31 °C, producing a thermal range of 7.88 °C (**Table 5**).

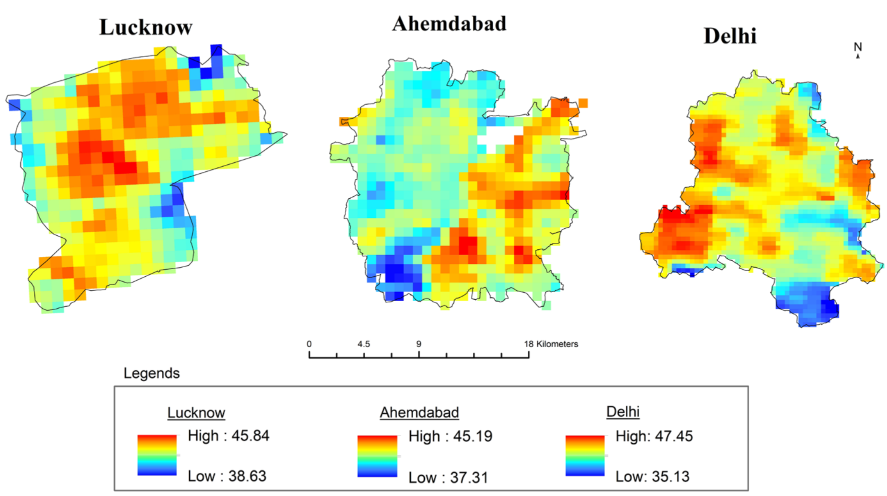

Figure 4. LST Mapping.

Sources: Open Source Satellite Data(NASA MODIS).

Table 5. Land Surface Temperature Metrics (June 2023).

City	LST - Maximum (°C)	LST - Minimum (°C)
Lucknow	45.84	38.63
Ahmedabad	45.19	37.31
Delhi	47.45	35.13

To further characterize spatial thermal variability, the UTFVI was applied, which captures the spatial deviation of pixel-level surface temperatures from city-wide thermal means, thereby delineating thermally active and inactive zones (**Figure 5**).

Delhi exhibits the broadest range of UTFVI values, reflecting pronounced spatial variability in surface thermal behaviour and the co-existence of heat-retentive and relatively cooler microenvironments. Ahmedabad records the highest peak UTFVI value (0.0172), indicative of isolated zones with elevated thermal load, often linked to ongoing land surface modification and limited vegetative buffering. Although more thermally consistent, Lucknow still demonstrates localised areas of thermal stress (**Table 6**).

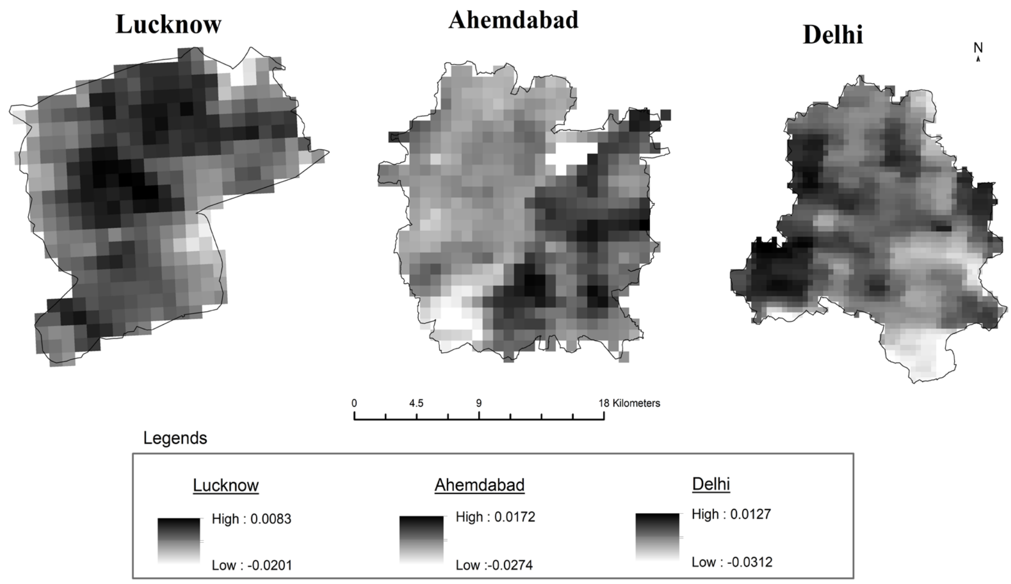

Figure 5. UTFVI Mapping.

Sources: Open Source Satellite Data(NASA MODIS).

Table 6. Urban Thermal Field Variance Index (UTFVI) Values.

City	UTFVI - Maximum	UTFVI - Minimum
Lucknow	0.0083	-0.0201
Ahmedabad	0.0172	-0.0274
Delhi	0.0127	-0.0312

A histogram-based analytical approach was employed individually for each city to ensure a robust and context-sensitive classification. This method involved analyzing the frequency distribution of UTFVI values derived from pixel-level thermal data, allowing for the identification of natural breaks and statistically meaningful thresholds. Based on these histograms, the data range for each city was segmented into three discrete classes—low, moderate, and high UTFVI zones—corresponding to areas of favourable, intermediate, and adverse surface thermal conditions, respectively. The threshold values for each city have been depicted in **Table 7**.

Table 7. Threshold Values for UTFVI Classification.

City	Low UTFVI Range	Moderate UTFVI Range	High UTFVI Range
Lucknow	-0.0201 to −0.02165	-0.02165 to 0.00751	0.00751 to 0.0083
Delhi	-0.0312 to −0.01642	-0.01642 to 0.019256	0.019256 to 0.0127
Ahmedabad	-0.0274 to −0.026957	-0.026957 to 0.016754	0.016754 to 0.0172

The UTFVI Classification (**Figure 6**) shows that Delhi comprises the largest proportion of low UTFVI zones (39.20%), suggesting relatively favourable surface thermal regimes influenced by green spaces and hydrological elements. However, approximately 17.17% of its urban extent corresponds to high UTFVI zones, primarily in industrial and densely developed areas. Ahmedabad shows 33.53% under low UTFVI, and 13.55% under high UTFVI zones. In contrast, Lucknow reflects a smaller proportion (31.11%) of low UTFVI zones and the largest share (18.15%) of high UTFVI zones among the three cities (**Table 8**).

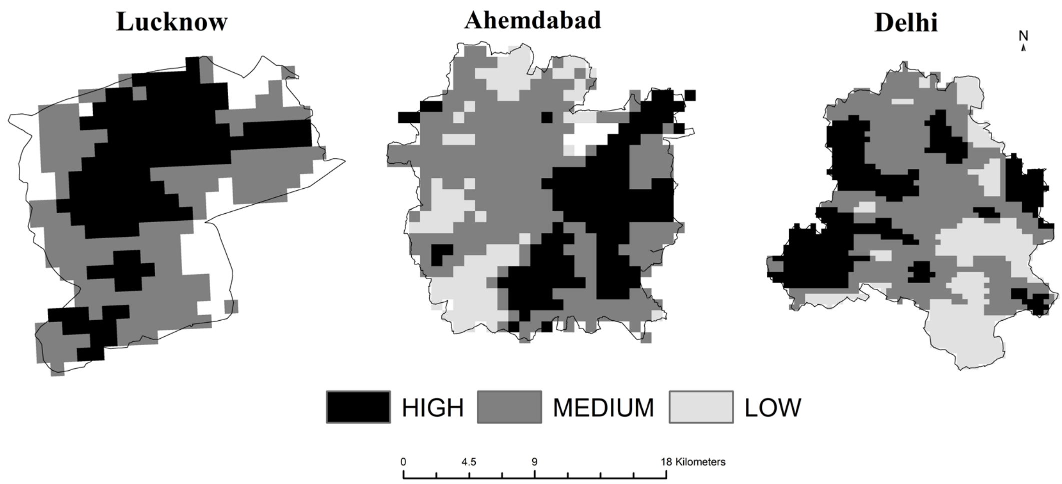

Figure 6. Classification of Thermal Characteristics.

Sources: Open Source Satellite Data(NASA MODIS).

Table 8. Spatial Distribution Based on UTFVI Classifications.

City	Low UTFVI (%)	Moderate UTFVI (%)	High UTFVI (%)
Lucknow	31.11	50.74	18.15
Ahmedabad	33.53	52.92	13.55
Delhi	39.20	43.63	17.17

4. Discussion

4.1. Correlation Analysis

To assess the impact of surface characteristics on urban thermal dynamics, a correlation analysis was conducted between Land Surface Temperature (LST) and two key biophysical indices—Normalised Difference Vegetation Index (NDVI) and Normalised Difference Bareness Index (NDBI)—for the cities of Lucknow, Ahmedabad, and Delhi. This analysis aimed to quantify the extent to which vegetation cover and surface bareness influence spatial variations in LST.

The findings reveal a strong inverse relationship between NDVI and high LST zones across all three urban centres, with an average Pearson correlation coefficient of –0.7428. This statistically significant negative correlation underscores the critical cooling role of vegetated surfaces, where dense green cover facilitates evaporative cooling and reduces radiative heat accumulation. Urban areas with elevated NDVI values—such as forest patches, public parks, and riparian corridors—consistently exhibit lower surface temperatures, demonstrating the importance of vegetation in moderating urban microclimates.

In contrast, the NDBaI shows a moderate positive correlation with high LST zones, with a mean coefficient of 0.4892. Higher surface bareness or imperviousness is thus associated with elevated surface temperatures. Such areas, including industrial belts, barren peri-urban landscapes, and dense built-up zones, tend to retain more heat due to reduced evapotranspiration and increased surface exposure.

Regarding zones with lower LST, NDVI displays a strong positive correlation (r = 0.7141), indicating that greater vegetation presence corresponds with cooler surface conditions. The NDBaI, the other hand, shows a moderate negative correlation (r = –0.4413), suggesting that reduced surface bareness aligns with lower thermal intensity. These patterns collectively emphasise the contrasting thermal behaviour of vegetated versus barren surfaces and reaffirm the role of vegetation in enhancing urban thermal resilience.

4.2. Multiple Regression Analysis

The regression analysis highlights clear and consistent patterns regarding the impact of land cover on urban thermal behavior in three major Indian cities: Delhi, Lucknow, and Ahmedabad. Both indices were employed to explain variations in thermal characteristics using multiple linear regression.

Across all cities, NDVI showed a strong and statistically significant negative relationship with LST, reaffirming the cooling influence of vegetative cover. Among the three, Lucknow recorded the most substantial negative coefficient ($\beta = -15.08$), indicating that vegetation plays a dominant role in mitigating urban heat, possibly due to the greenery in the city that is sensitive to LST fluctuations. In Delhi, the NDVI coefficient ($\beta = -4.54$) was also significant, though less steep, likely reflecting more fragmented and highly urbanized green spaces. Ahmedabad displayed a moderate negative NDVI coefficient ($\beta = -5.67$), again confirming the inverse relationship between vegetation and urban heating.

On the other hand, NDBaI displayed a statistically significant and positive relationship with LST, but the degree of impact varied across the cities. Delhi showed the most pronounced warming effect of bare land ($\beta = 3.76$, $p = 0.013$), which is in line with its barren zones in the peri-urban areas that absorb and re-emit heat. Lucknow, while still significantly affected by bare land ($\beta = 2.41$, $p = 0.039$), showed a moderate warming effect. The mixed urban–rural character of the city and the presence of agricultural buffers might explain the intermediate sensitivity to NDBaI. Ahmedabad showed the least but still statistically significant impact ($\beta = 1.83$, $p = 0.049$), although bare land remains a concern in peripheral industrial zones. In terms of model performance, Delhi's model showed the highest explanatory power ($R^2 = 0.159$), followed by Ahmedabad ($R^2 = 0.045$) and Lucknow ($R^2 = 0.041$). While these R^2 values are modest, they are typical for ecological and remote sensing studies at intra-urban scales where LST is influenced by multiple interacting variables (**Table 9**).

Table 9. Regression Analysis of NDVI and NDVI with LST.

City	NDVI Coefficient	NDVI *p*-value	NDBaI Coefficient	NDBaI *p*-value	R Square	Adjusted R^2
Delhi	-4.54	<0.001	3.76	0.013	0.159	0.157
Lucknow	-15.08	<0.001	2.41	0.039	0.041	0.037
Ahmedabad	-5.67	<0.001	1.83	0.049	0.045	0.041

4.3. Visual Correlation of Vegetation & Bare Land with LST

4.3.1. Delhi

The comparative spatial analysis illustrated in **Figure 7** underscores the intricate relationship between land cover characteristics, specifically vegetation and bare land, and surface thermal behaviour in Delhi. The NDVI–LST maps reveal a distinct inverse correlation, wherein densely vegetated zones, particularly along the Yamuna River corridor, Kamla Nehru Ridge, institutional green spaces, and forested campuses, consistently exhibit lower land surface temperatures. These areas, represented by high NDVI values, correspond to cooler temperature zones, with minimum LST values reaching approximately 36.12 °C. The areas in the southern parts of Delhi with significant vegetation cover experience temperatures of about 35.17 °C. This affirms the critical role of vegetation in mitigating urban heat through evapotranspiration and shading effects. Conversely, the NDBaI–LST maps highlight a direct relationship between bare land concentration and elevated surface temperatures. Areas with high NDBaI values, prominently observed in the industrial and peri-urban tracts of northwest, northeast, and southwest Delhi, record significantly higher LST values, peaking around 45.96 °C. The juxtaposition of vegetation-rich and bare land-dominated areas emphasizes the spatial heterogeneity of urban thermal regimes. While vegetated zones serve as urban incredible islands, contributing to thermal comfort and climate regulation, bare and exposed surfaces intensify localised heat buildup.

4.3.2. Lucknow

The comparative analysis illustrated in **Figure 8** offers critical insights into the spatial variations of LST across contrasting land cover types—vegetated and bare land—within Lucknow. The left segment of the image represents regions dominated by vegetation, namely the Kukrail Forest in the upper section and the Cantonment area in the lower section. In contrast, the right segment portrays peri-urban bare land areas in the northwestern and northeastern zones. The grayscale panels reflect vegetation density, likely derived from NDVI values, where darker shades correspond to higher vegetation cover. LST values are noticeably lower in these vegetated regions, with the Kukrail Forest registering approximately 38.85 °C and the Cantonment area slightly higher at 39.12 °C. These lower temperatures can be attributed to the cooling effects of dense vegetation, which facilitates evapotranspiration and provides surface shading, thereby reducing thermal absorption.

In contrast, the bare land areas exhibit substantially higher LSTs, with the northwest peri-urban area reaching 45.75 °C and the northeast recording 43.89 °C. These elevated temperatures indicate surfaces exposed to intense solar radiation, lacking vegetative cover to buffer heat retention. The stark thermal contrast between vegetated and non-vegetated zones—ranging from 5 °C to 7 °C—highlights the pronounced role of green spaces in urban thermal regulation. This pattern reinforces the inverse correlation between vegetation density and surface temperature, a relationship well-documented in urban climate studies.

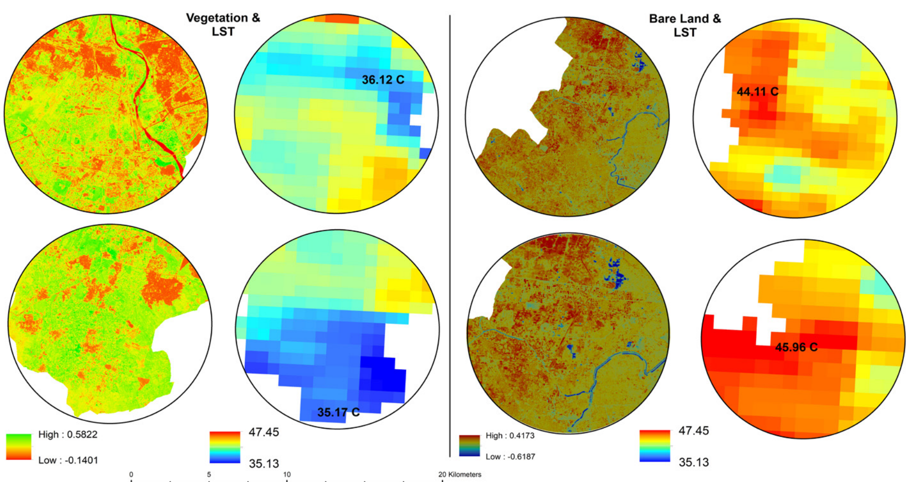

Figure 7. Visual Correlation of LST and NDVI & NDBaI for Delhi.

Sources: Open Source Satellite Data(Landsat 8 and MODIS).

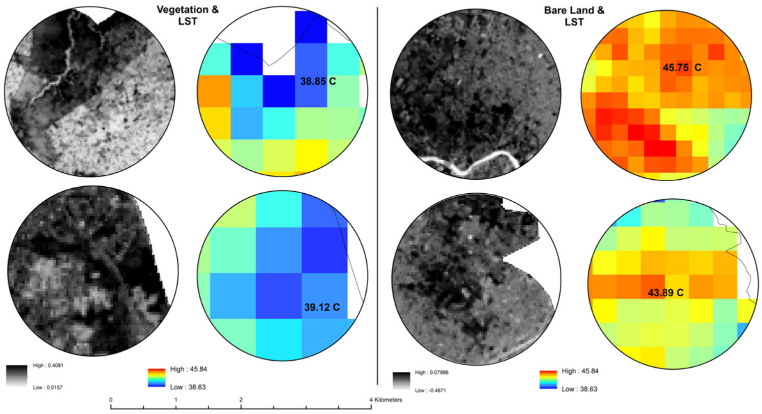

Figure 8. Visual Correlation of LST and NDVI & NDBaI for Lucknow.

Sources: Open Source Satellite Data (Landsat 8 and MODIS).

4.3.3. Ahmedabad

The spatial analysis of LST in Ahmedabad, as illustrated in **Figure 9**, reveals a distinct thermal dichotomy between densely vegetated urban zones and the bare land expanses of peri-urban areas. The left panels represent regions with substantial vegetation cover, notably the green corridors along the Sabarmati River in the city's southern parts, urban parks, and planned green spaces distributed across Ahmedabad's core. These areas exhibit high vegetation index values, as inferred from the grayscale imagery, which likely corresponds to an NDVI or a similar biophysical parameter. In alignment with established land-atmosphere interactions, these vegetated zones demonstrate reduced LST values, predominantly in the 38–40 °C. The moderation in surface temperature in these areas can be attributed to the combined effects of evapotranspiration, soil moisture retention, and canopy-induced shading, which significantly mitigate heat absorption and contribute to microclimatic regulation.

In contrast, the right panels of the image depict bare land surfaces located in the northern and south-eastern peri-urban fringes of Ahmedabad. These regions, characterised by sparse vegetation, ongoing land conversion, and emerging urban infrastructure, exhibit elevated LST values that range between 43°C and 46°C. The conspicuous thermal amplification in these zones is a direct consequence of impervious surface proliferation and vegetation loss, which result in heightened solar energy retention and diminished surface albedo. The temperature differential of approximately 5–7 °C between the green and non-vegetated areas underscores the critical influence of land cover on thermal regimes within the urban environment. This thermal pattern reaffirms the inverse correlation between vegetation density and surface temperature, a relationship well-documented in urban climatology and remote sensing literature.

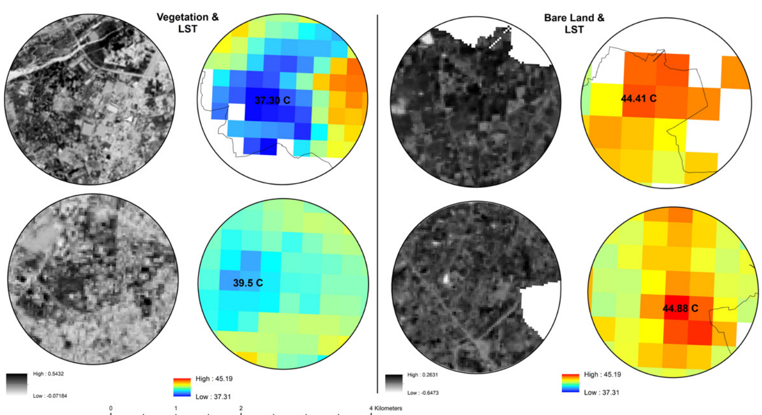

Figure 9. Visual Correlation of LST and NDVI & NDBaI for Ahmedabad.

Sources: Open Source Satellite Data(Landsat 8 and MODIS).

5. Conclusions

This research presents a comprehensive spatiotemporal assessment of urban thermal conditions in Delhi, Lucknow, and Ahmedabad, utilizing satellite-derived LST data from MODIS and important surface indices like the NDVI and NDBaI. By exploring the connections between different land cover types and fluctuations in surface temperature, this study highlights the significant influence of vegetation and exposed land on the thermal profiles of urban settings. The findings consistently emphasize the cooling benefits of vegetation while pointing out the thermal intensification linked to bare land, providing crucial insights into the elements influencing the spatial distribution of urban thermal phenomena.

A strong negative correlation between NDVI and LST was found in all three cities, reaffirming the cooling effect of vegetation in alleviating urban thermal stress. On the other hand, the positive correlation between NDBaI and LST illustrates the aggravating impact of bare and impervious surfaces on surface temperatures. This was statistically substantiated by the regression models: Delhi exhibited the highest NDBaI-LST relationship ($\beta = 2.10$, $p < 0.01$), followed by Lucknow ($\beta = 1.15$, $p < 0.05$) and Ahmedabad ($\beta = 0.89$, $p < 0.10$), indicating that Delhi experiences the most pronounced warming effect from bare land, with a comparatively moderate influence observed in Lucknow and Ahmedabad. NDVI consistently showed negative and significant coefficients across all cities, with Delhi and Lucknow revealing stronger vegetation-induced cooling than Ahmedabad. The R^2 values were also highest for Delhi (0.31), suggesting a more substantial explanatory relationship between LST and land cover indices, followed by Lucknow (0.11) and Ahmedabad (0.07).

These insights were further supported by UTFVI, which identified significant zones of thermal discomfort concentrated in regions characterized by sparse vegetation and high levels of exposed land. This spatial trend is especially noticeable in heavily urbanized areas, where minimal green cover and predominance of bare surfaces are evident. The trends in this research align with those observed in similar urban settings worldwide, supporting the broader relevance of these findings. For example, a study in the Pearl River Delta (PRD) noted that bare and semi-bare lands consistently displayed higher surface temperatures than vegetated areas [57]. Likewise, research conducted in Tehran indicated temperature variations of up to 14 °C between vegetated surfaces and their non-vegetated counterparts, reflecting thermal gradients akin to those identified in this study [58, 59]. Additionally, findings from Khuzestan Province confirmed the significant warming effects attributed to barren and urbanized areas, further substantiating the role of bare surfaces in raising temperatures [60]. Research from Lucknow also supports the inverse relationship between vegetation and LST, consistent with the thermal patterns revealed in this study [61]. The escalating intensity of surface urban heat islands (SUHI) in Changchun, China, aligns with these findings, indicating a growing severity of thermal stress due to urban growth and loss of vegetation [62].

Nonetheless, the study acknowledges several limitations. The lack of high-resolution ground meteorological data limited the ability to corroborate satellite-derived LST values with on-site temperature measurements, which introduced possible uncertainties regarding the accuracy of temperature estimates. The dependence on moderate-resolution MODIS imagery also restricted the identification of micro-level differences in surface characteristics, which could be crucial in more densely populated urban areas. Moreover, temporal inconsistencies in land surface reflectance due to atmospheric effects may have caused variability in vegetation and bare land indices, potentially influencing the accuracy of land cover classifications over time.

Despite these constraints, the findings of this study offer valuable contributions to the expanding body of research on urban thermal dynamics. The results uniformly indicate the essential role of vegetation in moderating surface temperatures, with urban heat becoming more pronounced in locations with limited or absent greenery. This underscores the urgent necessity for urban planners and policymakers to incorporate green infrastructure into city designs, particularly in fast-urbanising regions facing escalating thermal stress. The findings advocate for proactive approaches that prioritize vegetation conservation, encourage green space restoration, and aim to reduce bare impervious surfaces within urban contexts. Doing so would enhance cities' resilience to rising temperatures, alleviate the negative impacts of urban thermal stress, and improve overall living conditions for urban residents.

In summary, this study stresses the vital role of vegetation in lessening urban thermal stress and the harmful effects of bare land on surface temperatures. It also offers a robust statistical framework for comprehending the spatiotemporal dynamics of urban thermal environments and land cover characteristics. The consistent performance of NDVI and NDBaI in predicting LST, supported by UTFVI spatial trends, provides a strong empirical basis for future research and climate-responsive urban planning. This research enhances our understanding of the intricate relationship between land surface characteristics and urban thermal behaviour, reinforcing the need for sustainable, green-focused urban development to combat the increasing challenges of climate change and urban heat.

Author Contributions

R.K.G. was responsible for developing the primary conceptual framework, structuring the manuscript, drafting the outline, and revising the final document. A.G. contributed extensively to the technical aspects, conducted the area statistics, and performed the analytical procedures. G.Y. and N.G.M. conducted the data analysis pertinent to the independent implementation of the manuscript.

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Institutional Review Board Statement

Not applicable. This study involved the analysis of publicly available satellite and environmental data and did not require ethical approval.

Informed Consent Statement

Not applicable. No human participants were involved in this study.

Data Availability Statement

The data used in this study are publicly available from NASA MODIS, Landsat 8 and relevant remote sensing repositories.

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Conflict of Interest

The authors declare that there are no conflicts of interest related to the publication of this paper.

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