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Effect of Land Use on Daytime Climatic Comfort in High-Rise Urban Developments in Delhi

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ABSTRACT

This research offers valuable insights into the relationship between land use and daytime climatic comfort in high-rise urban developments in Delhi. This city is navigating rapid urbanisation and facing critical environmental challenges like pollution, heat stress, land degradation etc. The study aims to enhance understanding of how diverse land use patterns influence thermal comfort by utilising satellite data from the Landsat/Resourcesat series for classification and MODIS for land surface temperature (LST) extraction. The findings highlight that regions with dense construction and limited green and blue spaces tend to experience lower levels of climatic comfort, with 17.17 Percent of Delhi's geographical area feeling the adverse effects of the Urban Heat Island (UHI) phenomenon. On a positive note, 40.20 Percent of the area is associated with high climatic comfort, primarily due to natural features such as vegetation and water bodies. Furthermore, the research indicates a noteworthy increase in land surface temperatures (LST) from 2000 to 2022, with peak recorded temperatures rising from 38.35°C in 2000 to 47.27°C in 2022. In summary, this study emphasises the importance of understanding and addressing the UHI effect in urban settings, providing constructive recommendations for policymakers and stakeholders dedicated to fostering improved livability and sustainability in urban environments.

Keywords: Land Use; Urbanisation; Climatic Comfort; GIS

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1. Introduction

Urban areas are increasingly facing challenges related to daytime climatic comfort due to the intricate interplay between land use patterns and climatic conditions. These challenges arise due to the rapid urbanisation of the cities, which results in significant changes in their land use. As urban areas expand vertically and horizontally, the implications of such developments on environmental factors, notably climatic comfort, become critical areas of study. Daytime climatic comfort, a key component of urban liveability, is profoundly influenced by various factors such as urban heat islands, microclimates, land use patterns, and green spaces [1–4]. Replacing natural surfaces with impermeable artificial ones disrupts the heat exchange processes between soil and the atmosphere [5,6], altering the daytime thermal comfort of cities. The configuration of urban developments, including vegetation and building densities, is crucial in shaping city thermal comfort levels [7]. An urban heat island (UHI) is a phenomenon characterised by a metropolitan area experiencing significantly higher temperatures than its surrounding rural areas [2]. This temperature difference is primarily attributed to the increased urbanisation and human activities within the city, leading to distinct heat islands with substantial temperature variations between urban and rural regions [2,8–10]. This results in elevated daytime temperatures, adversely affecting human health, energy consumption, and overall quality of life. The UHI effect is driven by a variety of factors, including the replacement of natural vegetation with impervious surfaces such as concrete and asphalt, which absorb and retain heat, as well as the heat generated by human activities such as transportation, industry, and energy consumption [11,12]. Additionally, urban areas often lack adequate green spaces and vegetation, further exacerbating heat retention and reducing opportunities for natural cooling through evapotranspiration [13].

Various studies have highlighted that the daytime thermal comfort in cities is a crucial factor that significantly impacts the well-being of urban residents [14–19]. Understanding and monitoring urban thermal comfort are essential for developing effective strategies to mitigate thermal stress and improve the overall quality of urban life [20]. By considering factors like urban morphology, microclimate, and environmental design, cities can optimise outdoor thermal comfort, thereby positively impacting the well-being of their inhabitants [21,22].

Geospatial techniques, incorporating GIS, Remote Sensing, GNSS, and other emerging technologies, have proven to be beneficial tools for studying phenomena related to the Earth's surface [19,23–25]. By applying these techniques, the features of attributes related to Land Use and daytime climatic comfort can be mapped, analysed, and interpreted efficiently.

However, despite the global proliferation of research on UHI and urban thermal comfort, a notable knowledge gap remains in the Indian context, particularly regarding the spatiotemporal analysis of land use dynamics and their direct impact on daytime climatic comfort. Existing literature often focuses on large metropolitan cores, while peri-urban and transitional zones—areas undergoing rapid and unplanned development—remain significantly understudied. Furthermore, few studies have concurrently analysed both land use and thermal comfort over time using integrated geospatial techniques. This study incorporates index-based methods to evaluate current land use conditions regarding thermal comfort, especially in Indian urban landscapes. Such an approach can provide standardised, quantitative insights into how specific land use types contribute to or mitigate heat stress in urban areas.

In this context, the present study addresses these gaps by examining the temporal relationship between land use and land cover (LULC) changes and daytime climatic comfort in selected urban and peri-urban zones. The specific objectives of this study are as follows:

- To analyse the temporal changes in LULC patterns of Delhi from 2000 to 2022.
- To assess the temporal variation in daytime climatic comfort and surface temperature distribution from 2000 to 2022.
- To investigate the relationship between LULC dynamics and changes in urban thermal comfort over time.

These objectives aim to contribute to the growing body of knowledge in urban climate studies by providing empirical insights into the spatial and temporal interactions between land use dynamics and daytime climatic comfort, thereby supporting evidence-based urban planning and policy formulation.

2. Materials and Methods

2.1. Study Area

Delhi, situated in the northern region of India, serves as a pivotal hub within the National Capital Region (NCR). The city, which covers an expansive area of approximately 1,483 square kilometres, is at an average of 216 metres above sea level. Geographically, Delhi lies at a latitude of around 28.61 degrees North and a longitude of approximately 77.23 degrees East. Two prominent geographical features stand out within its confines: the fertile Yamuna floodplains that nourish the area and the arid Delhi Ridge, a natural barrier regulating the city's climate. The climate of Delhi is classified as semi-arid, exhibiting distinct and pronounced seasonal variations. The summer months, from April to June, can be particularly oppressive, with temperatures frequently exceeding 40°C (104°F) during peak heat. This intense heat often leads to dry and dusty conditions across the city. The monsoon season, from July to September, dramatically transforms the landscape. During this period, the city receives approximately 80 percent of its annual rainfall, vital for replenishing groundwater and sustaining the region's agriculture. Conversely, the winter months from December to February bring cooler weather, with temperatures sometimes plummeting to near freezing, reaching lows of around 5°C (41°F) or even lower in some areas. Delhi is home to a staggering population of approximately 16.35 million residents, making it one of the most populous cities in the world. This diverse metropolis reflects a rich tapestry of cultural and historical influences, showcasing various architectural styles and urban landscapes. Visitors and locals alike can explore its iconic ancient monuments, such as the Red Fort and Humayun's Tomb, vibrant local markets filled with artisanal crafts and street food, and government edifices that symbolise its political importance. The juxtaposition of modern skyscrapers and bustling commercial areas with historical sites illustrates Delhi's unique blend of tradition and contemporary development.

2.2. Datasets Used

The present study employed a range of remotely sensed geospatial datasets obtained from credible open-access platforms, including the USGS Earth Explorer, Bhuvan (ISRO), and NASA EarthData, to investigate the spatial and temporal dynamics of land use and daytime climatic comfort across the Delhi region (**Table 1**). Multiple satellite missions were used to ensure data reliability, spatial-temporal consistency, and thematic relevance. The years 2000 and 2022 were selected to provide a comprehensive temporal analysis spanning over two decades, capturing the long-term trends in land use and climatic comfort changes in Delhi. The year 2000 represents the turn of the millennium, serving as a baseline before rapid urban expansion intensified. At the same time, 2022 reflects the most recent available data, enabling an up-to-date assessment of current land use patterns and thermal conditions. This period allows for evaluating the cumulative impact of urbanisation and policy interventions on the city's environment and supports informed planning for future sustainable development. The availability of consistent and high-quality satellite datasets for these years facilitated robust comparative analysis.

Table 1. Datasets Used.

Satellite	Spatial Resolution	Bands	Sensor	Time	Cloud Cover	Source	Utility
Landsat 7	30 m	1 to 5; 7–8	ETM+	June 2000	Less than 30%	USGS Earth Explorer	LULC Mapping
Resourcesat 2	23.5 m	1 to 4	LISS III	June 2010	Less than 30%	Bhuvan	LULC Mapping
Landsat 8	30 m	Bands	OLI & TIRS	June 2023	Less than 30%	USGS Earth Explorer	LULC Mapping; Index Mapping
MODIS	1 km		Terra	June 2000 June 2010 June 2022	Less than 30%	NASA Earth Data	LST Mapping

For land use/land cover (LULC) mapping, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data from June 2000 were employed. Despite its utility, Landsat 7 is known to have experienced scan line corrector (SLC) failure post-2003, which introduced data gaps and striping. To address these limitations, Resourcesat-2 LISS-III data with a spatial resolution of 23.5 meters and minimal cloud cover were utilised for the intermediate year (June 2010), offering continuous spatial coverage and reliable LULC classification capabilities. This substitution ensures consistency in spatial analysis during the temporal gap caused by Landsat 7's limitations.

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) data from June 2022 were employed for both updated LULC mapping and the derivation of spectral indices to assess current land surface conditions. With its 30-meter spatial resolution and improved radiometric quality, Landsat 8 facilitated precise classification and surface analysis for the most recent time point. Band 3 (Green: 0.53–0.59 µm) and Band 5 (Near Infrared: 0.85–0.88 µm) were used to compute the Normalized Difference Vegetation Index (NDVI), which reflects vegetation health. The Modified Normalized Difference Water Index (MNDWI) was derived using Band 3 (Green) and Band 6 (SWIR1: 1.57–1.65 µm) to enhance the identification of surface water bodies. The Normalized Difference Built-up Index (NDBI) was calculated using Band 6 (SWIR1) and Band 5 (NIR) to identify built-up areas. Importantly, the Normalized Difference Bareness Index (NDBaI), which is effective for identifying bare or sparsely vegetated land, was computed using Band 6 (SWIR1) and Band 10 (Thermal Infrared, TIR: 10.60–11.19 µm), incorporating surface reflectance and thermal properties for better differentiation of bare surfaces. To complement and validate thermal analyses across temporal spans, MODIS Terra land surface temperature (LST) data were incorporated for the years 2000, 2010, and 2022. Although MODIS data have a coarser spatial resolution of 1 kilometre, their high temporal frequency and consistent thermal measurements enabled robust temporal comparison of urban heat conditions. All satellite images were atmospherically corrected using Level 2 surface reflectance and surface temperature products when available. These datasets were subsequently clipped to the official municipal boundaries of the study area using vector shapefiles from the Survey of India, thereby ensuring spatial precision and minimising edge-related artefacts during geospatial analysis.

2.3. Methodology

The methodology primarily involves the use of geospatial databases, tools, and techniques. Satellite data for calculating the Land Surface Temperature (LST) has been obtained from the MODIS Terra Satellite, which provides LST data products with a 1 km spatial resolution. The Brightness temperatures of the Land are measured by the satellite sensors onboard. These brightness values can be converted into the LST using the following formula (for the MODIS Terra Sensor) in GIS:

$$\text{Temperature in } ^{\circ}\text{C} = \text{DN} * 0.02 - 273.15 \tag{1}$$

where DN is the Digital Number of the MODIS Land Surface Temperature Satellite Data Product.

Since LULC is essential in determining the LST, the LULC maps of various temporal resolutions have been constructed using the IRS Resources/ Landsat Satellite Data products. Supervised classification using a maximum likelihood classifier has been utilised to categorise Delhi's Land uses into built-up, vegetated land, bare Land, water bodies, and forests from 2000 to 2022.

Indices such as the Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Normalised Difference Built-Up Index (NDBI), and Normalised Difference Bareness Index (NDBaI) have also been incorporated into the study for 2022 to examine various Land Surface characteristics.

(i) Urban Thermal Field Variance Index (UTFVI): The UTFVI plays a prominent role in ecologically evaluating the Urban Environment by considering the LST. It considers the impact of the LST at different locations on the overall mean LST of the urban area. Using LST, the UTFVI index was used to study Delhi's climatic comfort zones [26,27]. It is calculated by

$$\text{UTFVI} = 1 - \left(\frac{\text{LSTMean}}{\text{LSTPixel}}\right) \tag{2}$$

LST is the land surface temperature obtained from satellite data using MODIS Terra. $\text{LST}_{\text{Pixel}}$ is the Pixel value of the LST of different locations, and LST_{Mean} is the Mean value of the Whole urban area considered.

The Landsat datasets were utilised for calculating the various indices for studying and analysing the Land use of Delhi, which are described below:

(ii) Normalised Difference Vegetation Index (NDVI): The NDVI incorporates the Red and Infrared bands of the satellite data products to delineate the Vegetation cover at a particular location from its surrounding land uses[28–31]. It is calculated by

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

$$\text{NDVI for Landsat 8} = \frac{\text{Band 5} - \text{Band 4}}{\text{Band 5} + \text{Band 4}} \quad (4)$$

(iii) Normalised Difference Built-Up Index (NDBI): The NDBI utilises the Middle Infrared Ranges and Near Infrared ranges to differentiate the Built-up areas from other features. It is calculated by[32]:

$$\text{NDBI} = \frac{\text{Short wave Infrared} - \text{Near InfraRed}}{\text{Short wave Infrared} + \text{Near InfraRed}} \quad (5)$$

$$\text{NDBI for Landsat 8} = \frac{\text{Band 6} - \text{Band 5}}{\text{Band 6} + \text{Band 5}} \quad (6)$$

Modified Built-up Index (MBI): An improved and modified approach gives better results for extracting the Built-Up Land and is calculated by He, et al.[33]:

$$\text{MBI} = \text{NDBI} - \text{NDVI} \quad \text{MBI} = \text{NDBI} - \text{NDVI} \quad (7)$$

(iv) Normalised Difference Bareness Index (NDBaI): The NDBaI utilises the Middle-range Infrared and Thermal range bands to extract the Bare Land from the surrounding areas[34]. It is calculated by

$$\text{NDBaI} = \frac{\text{Short wave Infrared} - \text{Thermal}}{\text{Short wave Infrared} + \text{Thermal}} \quad (8)$$

$$\text{NDBaI for Landsat 8} = \frac{\text{Band 6} - \text{Band 10}}{\text{Band 6} + \text{Band 10}} \quad (9)$$

(v) Modified Normalised Difference Water Index (MNDWI): The MNDWI proves to be more effective in improving and extracting water-related information from within the nearby built-up environment or other Land uses as it can minimise or eliminate noise from built-up Land. This feature sets it apart from the NDWI[35]. It is calculated by

$$\text{MNDWI} = \frac{\text{Green} - \text{Short wave Infrared}}{\text{Green} + \text{Short wave Infrared}} \quad (10)$$

$$\text{MNDWI for Landsat 8} = \frac{\text{Band 3} - \text{Band 6}}{\text{Band 3} + \text{Band 6}} \quad (11)$$

3. Results

The expansion of Delhi has led to significant changes in land use patterns, converting fallow Land, agricultural areas, and vegetation cover into built-up urban zones (**Table 2**).

Table 2. Land Use and Land Cover.

	2000		**2010**		**2022**	
	Area (sq km)	**Percent**	**Area (sq km)**	**Percent**	**Area (sq km)**	**Percent**
Bare Land	190.9	12.9	120.6	8.1	98.1	6.6
Built-Up Land	485.6	32.7	702.6	47.4	825.6	55.6
Vegetation	565.4	38.1	480.7	32.4	398.2	26.8
Forest	208.9	14.1	148.6	10.0	131.6	8.9
Water Body	32.9	2.2	31.2	2.1	30.2	2.0
Grand Total	1483.6	100.0	1483.6	100.0	1483.6	100.0

Source: Open-Source Satellite Data.

The Built-Up Land in Delhi has experienced remarkable growth over the past couple of decades. In 2000, Built-Up Land spanned an area of 485.6 square kilometres, constituting approximately 32.7 percent of Delhi's total land area. This substantial expanse has significantly expanded, reaching 825.6 square kilometres by 2022. This represents an impressive increase of 70.2 percent, with its proportionate share rising to 55.6 percent. This dramatic surge highlights the extensive urbanisation and developmental activities that have been reshaping the urban landscape of Delhi, reflecting a shift towards more urban-centric living and infrastructure. Vegetation encompassing green spaces, such as parks, gardens, and agricultural lands, has declined. In 2000, vegetation covered 565.4 square kilometres, accounting for 38.1 percent of Delhi's overall land area. However, by 2022, this figure had dwindled to 398.2 square kilometres, marking a significant reduction of

29.6 percent. Consequently, its percentage share of the total area decreased to 26.8 percent. This decline can be primarily attributed to rapid urban expansion, pervasive deforestation, and shifts in land use patterns that prioritise urban development over green spaces and agricultural land. Forested areas in Delhi have seen a dramatic decrease during the same period. In 2000, forests covered 208.9 square kilometres, representing 14.1 percent of the total area. By 2022, this coverage diminished to just 131.6 square kilometres, indicating a substantial decline of 37 percent. This reduction also led to a decrease in its share of the city's total area to 8.9 percent, further exacerbating concerns over biodiversity loss and environmental degradation. The trend for Bare Land has also been downward from 2000 to 2022. In 2000, Bare Land encompassed 190.9 square kilometres, 12.9 percent of the total land area. This figure has plummeted to 98.1 square kilometres by 2022, reflecting a significant decrease of 48.6 percent. Its percentage share of the total land area has fallen to 6.6 percent. This trend further signifies the encroachment of urbanisation on previously open and undeveloped spaces, signalling a shift from natural landscapes to urban structures. Water bodies, including rivers, lakes, and ponds, have shown relatively stable trends amidst these significant LULC changes. In 2000, these aquatic areas occupied 32.9 square kilometres, constituting 2.2 percent of Delhi's total area. By 2022, this area had slightly decreased to 30.2 square kilometres, maintaining a percentage share of approximately 2.0 percent (**Figures 1** and **2**). This relative stability among water bodies denotes the importance of preserving these vital ecosystems amidst the pressures of urban development and environmental changes. The dynamics of land use in Delhi reflect a complex interplay between urban growth and ecological challenges, raising important questions about sustainability, conservation, and urban planning in the context of rapid urbanisation.

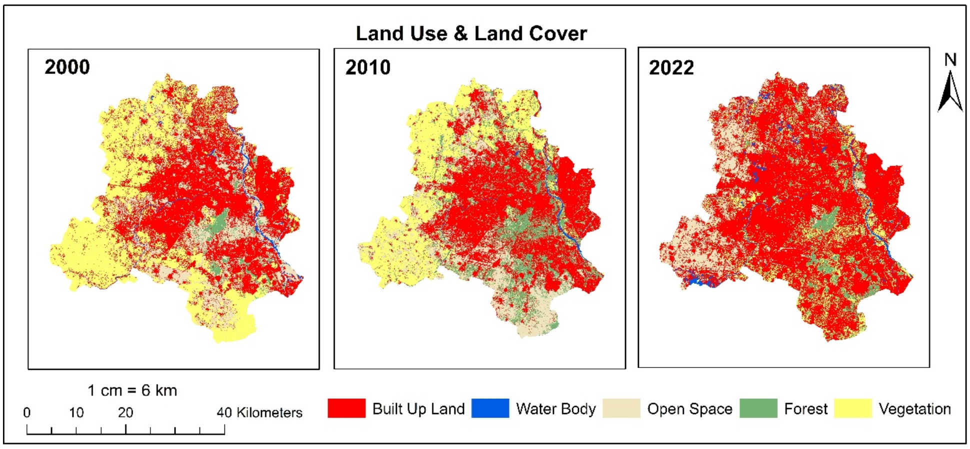

Figure 1. Land Use and Land Cover.

Source: Open-Source Satellite Data.

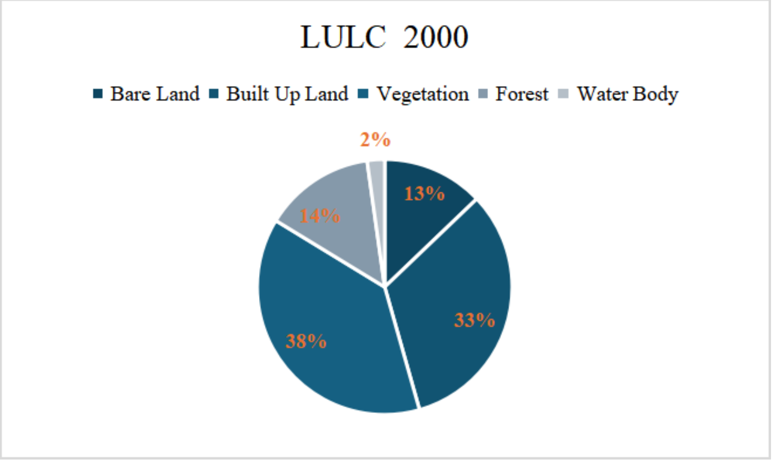

Figure 2. *Cont.*

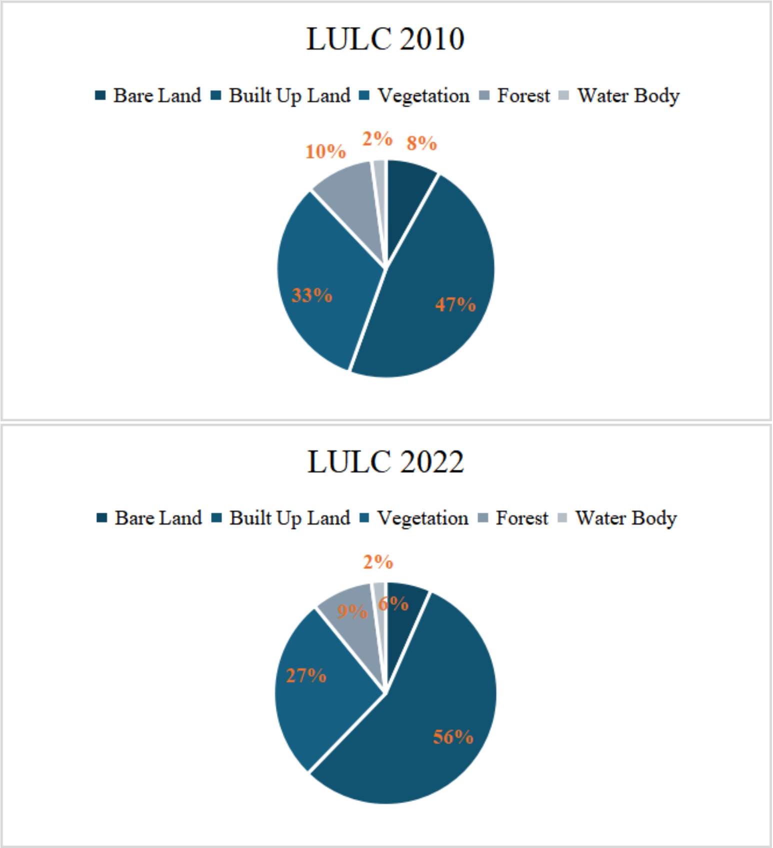

Figure 2. Land Use and Land Cover (Percentage).

Source: Open-Source Satellite Data.

An examination of LULC dynamics in Delhi between 2000 and 2022 reveals substantial transformations driven primarily by accelerated urbanisation. During the initial decade (2000–2010), the region underwent significant spatial reconfiguration marked by the extensive conversion of open and undeveloped areas into urban fabric. Bare land witnessed a marked reduction of approximately 70.29 km², indicative of its transformation into built-up zones. This shift corresponded with a substantial expansion of built-up land, which increased by 216.97 km², reflecting intensified infrastructural development spurred by economic growth and the rising demand for urban housing and services. However, this period of rapid urban expansion exerted considerable pressure on the region's ecological assets. Vegetation cover declined by 84.7 km², while forested areas contracted by 60.34 km², highlighting the environmental costs of unchecked urban growth. In contrast, water bodies exhibited relative stability, declining only marginally by 1.65 km², suggesting that surface hydrological features remained largely unaffected during this phase. In the subsequent period (2010–2022), LULC changes continued, though with varying intensities. The decline in bare land slowed, with a net loss of 22.55 km², while the built-up category continued its upward trajectory, expanding by 123.04 km². Notably, the degradation of green spaces remained a pressing concern. Vegetation cover further decreased by 82.5 km², and forest areas saw a reduction of 17.01 km². The continued loss of vegetative cover in the latter decade underscores the persistent imbalance between development and environmental preservation. Water bodies declined slightly by 1 km², reflecting ongoing pressures on aquatic ecosystems in the urban milieu. Cumulatively, the two-decade analysis underscores Delhi's profound urban transformation. Between 2000 and 2022, the city recorded a net decrease of 92.84 km² in bare land, reinforcing the trend of diminishing open spaces. Built-up areas experienced the most significant increase, growing by 340.01 km², which exemplifies the scale of urban sprawl and infrastructural intensification. Concurrently, vegetation and forest cover declined by 167.2 km² and 77.35 km², respectively, reflecting a notable depletion of natural landscapes. Though the total loss in water bodies was modest at 2.65 km², it nonetheless raises critical concerns regarding the long-term sustainability of water resources amid urbanisation pressures. This analysis underscores the urgent need for integrated urban planning strategies that reconcile developmental imperatives with ecological conservation. Without such measures, the continued expansion of built-up land may further compromise environmental sustainability and climatic resilience within Delhi's metropolitan landscape (**Figure 3)**.

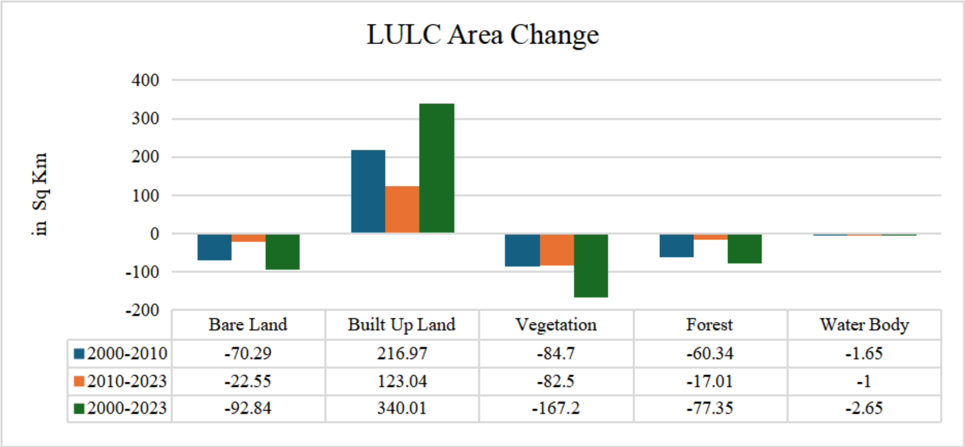

Figure 3. Land Use and Land Cover Change.

Source: Open-Source Satellite Data.

The analysis of land surface characteristics in Delhi for the year 2022 was conducted using a set of remote sensing-derived indices (**Figure 4, Table 3)**. The NDVI was employed to evaluate vegetation distribution and density across the region. High NDVI values, reaching up to 0.585, were observed in peri-urban areas along the Yamuna River and within ecologically significant zones such as Kamla Nehru Ridge and Yamuna Biodiversity Park. These areas represent approximately 28.29% of Delhi's total land area, reflecting the persistence of natural vegetation amidst extensive urban development. The MBI was used to assess urban infrastructure and built-up surfaces. Delhi exhibited an average MBI value of 0.328, with the highest concentrations found in densely developed neighbourhoods such as Paharganj, Chandni Chowk, and Karol Bagh. Built-up areas account for nearly 51.13% of the city's land, highlighting significant urban growth and increasing land consumption due to population pressures and infrastructural expansion. To identify surface water bodies, the MNDWI) was applied. Elevated MNDWI values, peaking at 0.315, were recorded along the Yamuna and Sahibi rivers and in water bodies such as Bhalswa Lake and the lakes within Yamuna Biodiversity Park. These features play a crucial role in supporting biodiversity and contributing to local thermal regulation in the urban microclimate. The NDBaI was calculated to detect barren or sparsely vegetated land surfaces. Values up to 0.423 were identified primarily in the northern, northwestern, and western fringes of the city, corresponding to peri-urban regions. These bare lands constitute approximately 12.14% of Delhi's total area, indicating zones affected by land degradation, underutilisation, or transition awaiting urban development. This index-based evaluation of vegetation, urban development, water presence, and bare land provides a comprehensive understanding of Delhi's heterogeneous land surface patterns, offering vital inputs for urban sustainability planning (**Tables 3** and **4**).

Table 3. Area Statistics of Satellite-Derived Indices.

Land Characteristics (Derived from Indices)	Percentage of Total Area	Location in Delhi
High Vegetation	28.29	Peri-Urban areas of Northern and Southern Delhi; Areas along Yamuna; Kamla Nehru Ridge, Model Town, Dhirpur Wetland, Yamuna Biodiversity Park, PUSA Hill Forest, Areas around JNU, NCR regions of Faridabad and Noida
High Built-Up	51.13	Areas of Shahdra and North East District include Sanjay Nagar, Uttam Enclave, Paharganj, Chandni Chowk, Karol Bagh, Patel Nagar, Patparganj, Ghaziabad, etc.

Table 3. *Cont.*

Land Characteristics (Derived from Indices)	Percentage of Total Area	Location in Delhi
High Waterbody	4.75	Yamuna River, Sahibi River, Bhalswa Lake, Yamuna Biodiversity Park Lake, Neeli Jheel, etc.
High Bare Land	12.14	Peri-urban areas of the North, Northwest, and West Districts, including Jhajjar and Gurgaon, as well as Bawana, Ladpur, and Bankoli.

Source: Open-Source Satellite Data.

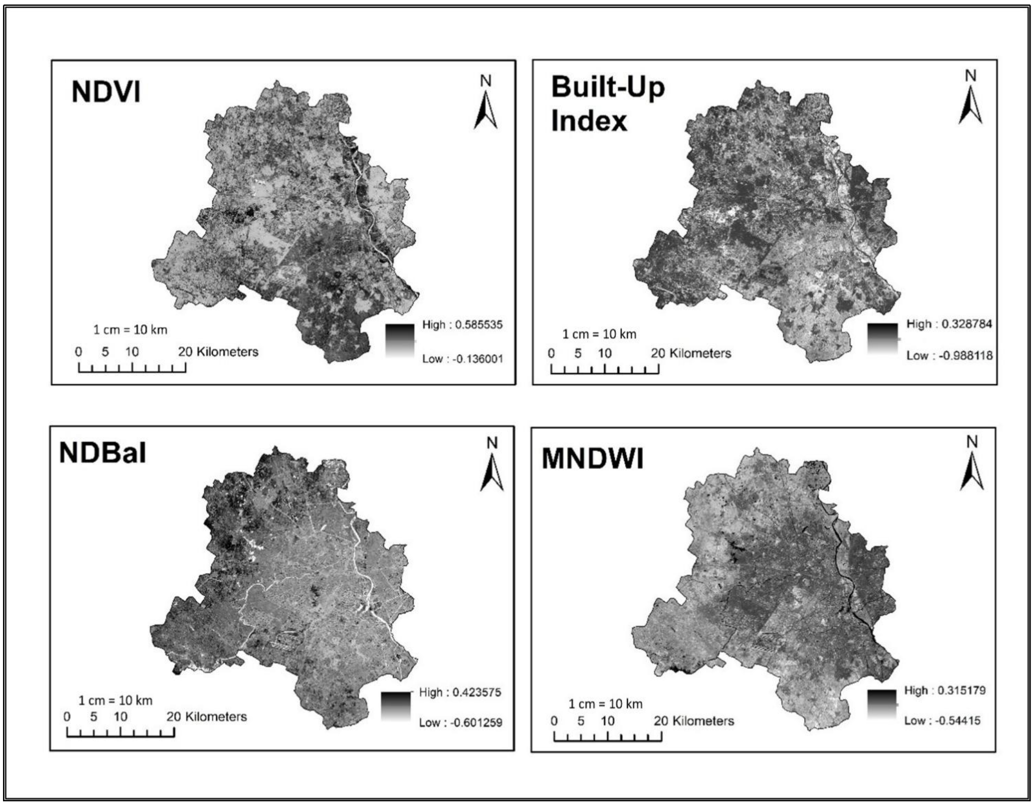

Figure 4. Satellite-Derived Indices (2022).

Source: Open-Source Satellite Data.

Table 4. Values of Indices.

Index	Delhi	
	Maximum	Minimum
NDVI	0.585	−0.136
MBI	0.328	−0.988
NDBaI	0.423	−0.601
MNDWI	0.315	−0.544

Source: Open-Source Satellite data.

Accuracy Assessment: Accuracy assessment was conducted for the LULC classification results of 2010 and 2022 using 80 stratified random sample points for each year. A confusion matrix was generated for both datasets, comparing classified land cover classes with reference data obtained through high-resolution satellite imagery and ground truth validation. The overall accuracy for 2010 was found to be 86.5%, while the classification results for 2022 demonstrated the highest accuracy, reaching 91.2%, indicating improved classification performance with higher-quality datasets and refined methodologies. The index-based classification of 2022, which incorporated spectral indices such as NDVI, MNDWI, MBI, and NDBaI, achieved an accuracy of 89.7%, further validating the reliability of multi-index approaches in enhancing classification precision (**Table 5)**.

However, due to the lack of high-resolution and reliable reference imagery for the year 2000, particularly in open-access platforms like Google Earth, an accuracy assessment for that year could not be performed. The limited availability of georeferenced historical imagery with precise dating posed a significant constraint for validating LULC classes. This represents a methodological limitation of the study, as the classification results for 2000 rely solely on unsupervised and rule-based techniques without ground-truth verification.

Table 5. Accuracy Assessment.

Year	Details	Overall Accuracy (%)	Kappa Coefficient (κ)
2010	LULC	85.2%	0.81
2022	LULC	90.8%	0.88
2022	Index-based Classification	89.6%	0.86

The temperature data for Delhi, spanning from 2000 to 2022, reveals a pronounced trend of rising temperatures over the years, illustrating the impacts of climate change in the region (**Figure 5**). In the year 2000, the maximum temperature recorded reached a peak of 38.35°C, while the minimum temperature was notably lower at 24.49°C, resulting in a temperature range of 13.86°C. By 2010, there was a significant increase in maximum and minimum temperatures; the former climbed to an impressive 41.99°C, and the latter rose to 31.61°C, indicating a growing heat intensity. This upward trajectory escalated dramatically by 2022, when the maximum temperature soared to an alarming 47.27°C, while the minimum temperature also increased to 32.93°C. This resulted in an expanded temperature range of 14.34°C, highlighting the increasing variability and severity of Delhi's climate conditions (**Table 6**). These figures underscore the rising trend of extreme heat events and point to potential implications for public health, urban infrastructure, and environmental sustainability in the face of ongoing global warming. The accuracy assessment of LST data could not be performed due to the unavailability of high-resolution, open-source meteorological station data for ground validation.

Table 6. Land Surface Temperatures of Delhi.

Year	LST-Maximum (in °C)	LST-Minimum (in °C)	Range (in °C)
2000	38.35	24.49	13.86
2010	41.99	31.61	10.38
2022	47.27	32.93	14.34

Source: Open-Source Satellite data.

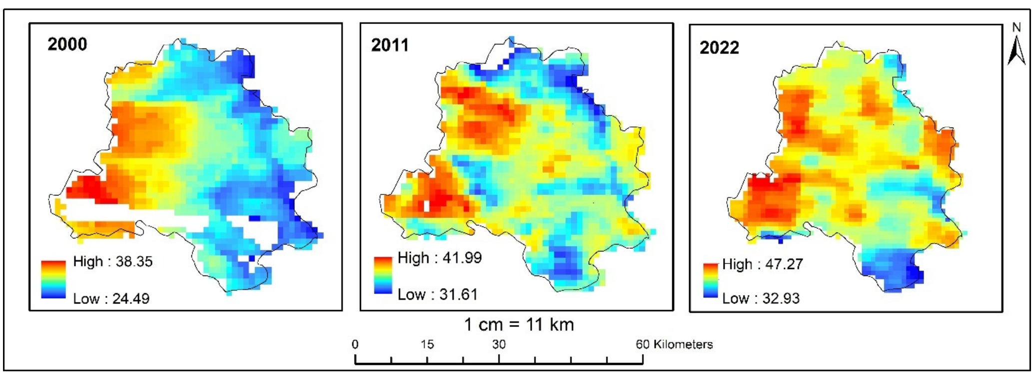

Figure 5. Land Surface Temperatures.

Source: Open-Source Satellite Data.

The analysis of spatial-temporal patterns of LST from 2000 to 2022 reveals a significant transformation in Central and East Delhi, where areas characterised by low LST have transitioned to those exhibiting high LST due to substantial urban expansion and changes in land use. Notable locations such as Patparganj, Shahdara, Anand Vihar, Jahangirpuri, Patel Nagar, Chandni Chowk, and Okhla recorded relatively low LST values in 2000 and 2010. However, these areas showed a marked increase in LST by 2022, reflecting urban development and heat accumulation.

To assess Delhi's Climatic Comfort, the UTFVI for the Delhi-NCR region was computed for 2022, utilising LST values derived from satellite imagery alongside mean LST values. The UTFVI results were classified into Low, Medium, and High Climatic Comfort Zones (**Figure 6, Table 7**). Notably, approximately 17.17 percent of the entire land area of Delhi is identified as a Climatic Comfort Zone, suggesting pockets where the urban heat island effect is mitigated. **Table 8** delineates specific locations of thermal comfort and discomfort, highlighting the areas of greater thermal discomfort that may benefit from targeted urban planning and greenery initiatives to enhance climatic comfort.

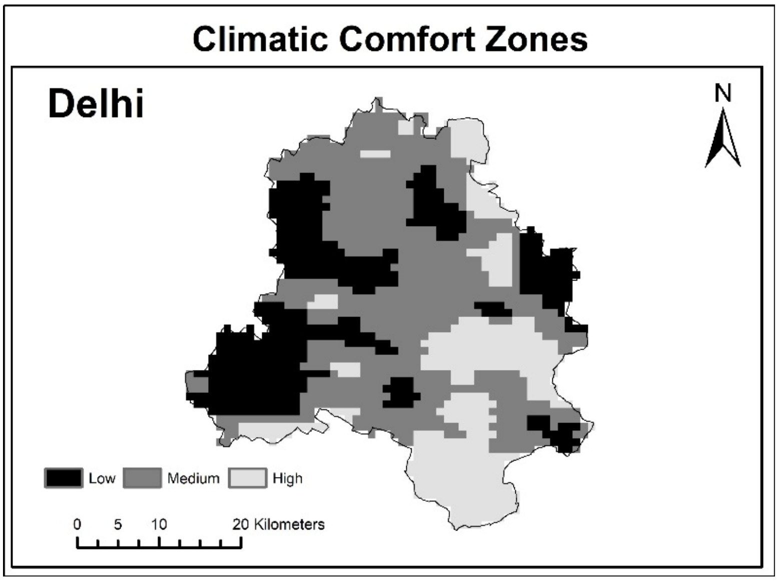

Figure 6. Climatic Comfort Zones (2022).

Source: Open-Source Satellite Data.

Table 7. Area Statistics of Comfort Areas (2022).

City	High Climatic Comfort (Percent of Total Area)	Moderate Climatic Comfort (Percent of Total Area)	Low Climatic Comfort (Percent of Total Area)
Delhi	40.20	42.63	17.17

Source: Open-Source Satellite Data.

Table 8. Locations of Comfort Zones.

City	Low Climatic Comfort Zones	High Climatic Comfort Zones
Delhi	Shahadra, Patparganj, Chandni Chowk, Karolbagh, Okhla Industrial Area, peri-urban in the form of barren Land on the west side of Delhi	Areas along the Yamuna River, Pusa Hill Forest, JNU, Kamla Nehru Ridge, Dhirpur Wetland, and Yamuna Biodiversity Park.

Source: Open-Source Satellite Data.

A quantitative comparison of LST across distinct land use classes reveals substantial thermal contrasts shaped by varying surface characteristics. In 2022, densely built-up areas such as East Delhi—comprising commercial zones, industrial sites, and high-density residential neighbourhoods—exhibited the highest LST values, peaking at 46.17°C. These urban cores, dominated by impervious surfaces and minimal vegetation, intensify the Urban Heat Island (UHI) effect due to heat retention and anthropogenic emissions. In contrast, vegetated and forested regions like Pusa, Jawaharlal Nehru University (JNU), and the Ridge Forest recorded significantly lower LSTs, ranging from 34°C to 36°C, reflecting the cooling influence of tree canopy cover and evapotranspiration processes. Similarly, water bodies such as the Yamuna River and its floodplains demonstrated the lowest LST values, approximately 33°C, underscoring the thermal regulatory role of surface water and moisture retention. Peri-urban barren lands in the western parts of Delhi, characterised by sparse vegetation and dry exposed soil, recorded LSTs of 43–44°C, highlighting their role in heat amplification due to high albedo and limited shading. In 2010, the emerging spatial heterogeneity in LST became more pronounced. Urban discomfort zones began to appear more visibly, particularly in central and northeastern Delhi, where LSTs reached a maximum of 41.99°C. This period marks the early development of UHI effects in the city centre, coinciding with increasing urbanisation and a decline in vegetative cover. By comparison, in the year 2000, the thermal landscape was more homogeneous. The maximum LST reached only 38.5°C, predominantly in West Delhi's barren lands, while the urban core had not yet developed significant UHI characteristics. Built-up regions during this time maintained relatively moderate temperatures, suggesting lower levels of heat stress and more balanced land use conditions.

4. Conclusions

This study offers critical insights into the dynamics of urban microclimates in Delhi, emphasising the influence of land surface characteristics on spatial temperature variability and thermal comfort. The analysis reveals a thermal discomfort effect across the city, with LST differences reaching up to 14°C in 2022. High LSTs were particularly evident in densely built-up and unplanned areas, such as East Delhi, where impervious surfaces dominate, green cover is sparse, and MBI values are high. These conditions exacerbate thermal stress, reduce pedestrian comfort, and elevate energy demand during peak summer months. Whereas areas with significant vegetation, such as the Pusa Hill Forest, Kamla Nehru Ridge, and Delhi Cantonment, exhibited markedly lower surface temperatures (34–36°C), demonstrating the cooling influence of green spaces. High NDVI values in these zones highlight the critical role of urban greenery in mitigating heat stress through shading, evapotranspiration, and reduced surface heat retention. Similarly, proximity to water bodies, as indicated by MNDWI values, provided localised cooling effects, particularly near the Yamuna River, underscoring the value of blue infrastructure in enhancing urban microclimates. The findings also indicate that elevated LSTs in built-up regions contribute to increased reliance on mechanical cooling systems, thereby intensifying energy consumption and greenhouse gas emissions. Vegetated and water-adjacent zones exhibit lower cooling loads, promoting energy efficiency and sustainability. The spatial correlations—negative between LST and NDVI, and positive between LST and NDBI—further validate the significance of land cover composition in shaping urban thermal environments.

The temporal and spatial patterns observed in Delhi align with broader national trends. This trend mirrors the multi-decadal satellite-based observations presented by Nayak et al. [36], who documented a statistically significant nighttime SUHI rise in Delhi, ranging from 2.04 to 3.7 °C between 2000 and 2023, particularly peaking during May, June, and July. Our findings corroborate this seasonal pattern, with elevated LST values during summer months and consistent warming trends in densely urbanised regions. A seasonal asymmetry in UHI intensity—where nighttime SUHI is more pronounced than daytime—also emerged in our analysis and corresponds well with Nayak et al.'s national-scale study [36]. This suggests the dominant role of heat retention in built-up surfaces and limited nocturnal cooling in Delhi's urban core, exacerbated by the loss of vegetative cover. The negative correlation between LST and NDVI, and positive correlation between LST and NDBI observed in this study, resonates with results from Chandigarh by Taloor et al. [37]. They reported a sharp summer LST rise from 32.42 °C in 2016 to 38.27 °C in 2020, and found that areas with lower NDVI values had consistently higher LST. Similar ecological stress patterns, as assessed via UTFVI in Chandigarh, reflect those in Delhi, particularly in dense commercial and industrial zones where over 30% of the land fell under the "worst" ecological category. This reinforces the need for LULC-sensitive urban planning and green buffer integration in Delhi's heat mitigation strategy. Comparative findings from Bhopal and Guwahati add a climatic and geographical dimension to the discussion [38]. While Bhopal displayed a cool island effect during summer daytime, attributed to its cropland-dominated periphery, Guwahati exhibited a typical positive SUHI. Our Delhi-centric analysis, showing consistent daytime and nighttime UHI effects, underscores how regional climate, land cover composition, and urban morphology mediate thermal anomalies. Notably, the study by Mohammad and Goswami highlights evapotranspiration and thermal inertia as key drivers [38], which also appear to influence Delhi's LST distribution, particularly where tree cover and water bodies are sparse. The study by Rani et al. in a sub-humid region emphasises the role of temporal LULC changes in amplifying UHI effects [39]. Their work supports our conclusion that expanding impervious surfaces and decreasing vegetation in Delhi have significantly contributed to the LST increase. Using satellite-derived NDVI and LST data, they highlighted the progressive shift toward warmer urban cores, echoing similar spatial shifts detected in our high-resolution LULC maps.

This study's high-resolution LULC analysis, supported by spectral indices, affirms that Delhi is among India's most thermally stressed metropolitan regions. It underscores the urgent need for climate-sensitive urban planning, including the integration of vegetative buffers, rooftop gardens, tree-lined streets, permeable surfaces, and the preservation of natural water bodies. Regulatory interventions—such as enforcing green building norms and incentivising energy-efficient design—are essential for creating thermally comfortable and resilient urban spaces. Despite its significant contributions, the study acknowledges several methodological limitations. LST analysis was conducted using single-date, summer-season satellite imagery for each reference year, limiting the ability to assess seasonal thermal variability. The use of medium-resolution imagery may have overlooked micro-scale thermal contributors such as narrow streets, small green patches, and rooftop vegetation. The absence of high-resolution reference imagery for the year 2000 restricted the accuracy assessment of historical LULC classification, and the lack of ground-based meteorological data prevented validation of satellite-derived LST. Future research should prioritise multi-seasonal and multi-year thermal analysis using high-resolution satellite data and ground-based observations to improve the accuracy, depth, and applicability of urban heat studies. Such enhancements would offer a more comprehensive understanding of intra-urban climatic variation and better inform evidence-based strategies for sustainable and climate-resilient urban development.

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Institutional Review Board Statement

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Informed Consent Statement

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Data Availability Statement

The Satellite data for this study were obtained from open, publicly accessible platforms, including the USGS Earth Explorer (https://earthexplorer.usgs.gov) and NASA's Earthdata portal (https://earthdata.nasa.gov), according to their data use policies.

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Conflicts of Interest

The author declares no conflict of interest.

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