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Assessment of Urban Green Space Dynamics Influencing the Surface Urban Heat Stress Using Advanced Geospatial Techniques

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Abstract: Urban areas are mostly heterogeneous due to settlements and vegetation including forests, water bodies and many other land use and land cover (LULC) classes. Due to the overwhelming population pressure, urbanization, industrial works and transportation systems, urban areas have been suffering from a deficiency of green spaces, which leads to an increase in the variation of temperature in urban areas. This study investigates the conceptual framework design towards urban green space (UGS) and thermal variability over Kolkata and Howrah city using advanced remote sensing (RS) and geospatial methods. The low green space is located in the highly built-up area, which is influenced by thermal variations. Therefore, the heat stress index showed a high area located within the central, north, northwestern and some parts of the southern areas. The vegetated areas decreased by 8.62% during the ten years studied and the other land uses increased by 11.23%. The relationship between land surface temperature (LST) and the normalized difference vegetation index (NDVI) showed significant changes with $R^2$ values between 0.48 (2010) and 0.23 (2020), respectively. The correlation among the LST and the normalized difference built-up index (NDBI) showed a notable level of change with $R^2$ values between 0.38 (2010) and 0.61 (2020), respectively. The results are expected to contribute significantly towards urban development and planning, policymaking and support for key stakeholders responsible for the sustainable urban planning procedures and processes.

Keywords: urban climate; urban green space (UGS); heat stress; geospatial indicators; twin city of West Bengal
1. Introduction

The earth’s forest and underlying vegetation provides a wide range of living options for human life [1,2]. However, issues of overcrowding, pollution and rapid urbanization are some threats to the existence of forest and vegetation [3]. A healthy ecosystem can enable greater long-term development by ensuring climate stability, flood control, freshwater availability, soil moisture control and soil erosion management [4,5]. Among the major contributors to greenhouse gas emissions (GHGE) are deforestation and vegetation degradation; they also contribute to urban heat and oxygen scarcity [6]. Rapid climatic change can disrupt the photosynthetic process and vegetation plays an active part in global climate change [7]. Forest and natural ecosystem protection to minimize greenhouse gas emissions has become an important aspect of global environmental protection in recent decades [8]. Numerous changes in external environmental conditions have impacted the vegetation development with various dynamic properties [9]. Population pressure is a major contributor to climate change in India [10]. Studies on climate change in India normally focus on climatic parameter analysis. Damage to the vegetation and the high temperature of the southern altitude areas are major contributors to the Indian subcontinent’s climatic changes [11]. Mountainous forests, on the other hand, are far more influenced by climate change [12,13]. Results of the long-term monitoring of forest conditions showed an improvement in air conditions and precipitation seasonality in this area [14,15]. Vegetation distribution in India is affected by LST, monsoons and precipitation [16]. To attain sustainable and continued health growth, vegetation requires adequate hydration, rain, soil conditions and a reasonably comfortable temperature [17]. The surface urban heat island (SUHI) variation, also derived from LST data, and the effect of vegetation deforestation have also been identified [18]. The further development of buildings has increased in megacities, providing an avenue for future research on the resulting impacts on vegetation and forests [19]. The population density, growth in the transportation sector and urban areal industrial works have also amplified pollution in metropolitan and industrial areas [20]. Researchers in many parts of the world have noticed considerable urban expansion associated with thermal variations and ecological disturbances in such locations. There is some literature that indicates that the study of urban heat islands and their impacts on the earth’s surface is becoming important [21–27]. Urban green space is also affected by urban expansion and increasing pressures from population growth [28–30]. Researchers found that urban expansion has also been affecting cities in Bangladesh and that study shows that urban expansion, thermal variation and vegetation dynamics can be inter-related [31]. In India, the cities of New Delhi, Mumbai, Chennai, Jaipur, Bilaspur and some others cities also demonstrate similar results as previous studies, particularly showing that anthropogenic activities could be the main reason for changes in green space dynamics and heat stress concerning these areas [32–35].

Concerning a study of the greater Kolkata area, results showed that most of the influences were from urban expansion and population pressures, especially where agricultural land, vegetation and water bodies were located [36]. The south Kolkata location was also affected by the huge amount of vegetation dynamics, where built-up land had expanded towards the south and the northeast location [37]. Some research also reported predictions of the urban thermal field variation index (UTFVI) for future environmental impact assessments in Bangladesh, where ecological disturbances were deduced using the UTFVI and machine learning methods [31]. Another research study aimed to identify urban expansion and population pressure on the capital city of India, Delhi, showing increases in the surface temperature and vegetation dynamics [38]. Green space plays a vital role in healthy living [39]. The urban heat waves have increased global warming and climate change worldwide [40]. The SUHI has also increased the thermal variations in different land use and land cover (LULC) classes [27]. Temperature has also been amplified in cities like Kolkata and Howrah Municipal Corporation area [41] and the Landsat 8 OLI/TIRS thermal bands data were used for mapping, examining and monitoring the land surface variation in the study area. Urban green space improved the environmental situation...
by contributing to healthier air quality conditions in the study area. Rapid urbanization increased the deficiency of ecological, economic and social conditions in India. The urban green space of this area is comprised of many parks, gardens, forests and related vegetation area classes [28]. Green spaces improve public health-related problems, social solidity, air pollution, climate change mitigation and ecological conservation [30,35]. Urban green spaces decreased vulnerabilities [28]. Research studies concerned urban green monitoring and associated management strategies [30,42–44]. Effective urban planning and management address unplanned urban expansion and increases in population pressure, both of which influence heat stress, vegetation dynamics, soil moisture, air pollution and some health emergencies [45].

Kolkata is one of the most populated cities in India, where urban expansion, building construction and vegetation degradation are the common reasons for a deficiency of urban green space. The adjacent city Howrah is also an overpopulated city and has a busy railway station named Howrah Railway Station. The business hub Kolkata is mostly urbanized and temperatures within this area have increased continuously. This has led to an increase in climate change variation. The municipalities have initiated the building of parks, gardens and many other vegetated areas, reflecting positive changes in the planning and management strategies aimed at promoting environmental and human health. Vegetation planting near roadways and metro stations was also initiated, but the overwhelming construction of buildings continues to decrease urban green space areas in many neighborhoods. The increased popularity of nuclear families is also one of the reasons for green space deficiency, because of the high demand for more small flats.

Green spaces such as parks and gardens increase fresh air quality and the contact of citizens with nature, leading to an enhanced environmental awareness of sustainable urban health. Peri-urban areas are also important for a healthy life, but due to population pressure, fringe regions such as Rajpur-Sonarpur, Habra, Joka and Moheshataka are becoming more built up.

High-resolution RS techniques have been used to capture images which are then used to determine the earth’s dynamic changes for many years as this helps with regional planning including human habitat planning [46]. An artificial neural network-based remotely sensed method was presented for the detection of changes in real-time applications [47,48]. The vegetation in Kolkata and Howrah had been severely damaged due to urban expansion, population pressure, industrial development and transportation accessibility. If this area does not recover soon, developments will have a negative influence on the coastal ecology and general climate.

The main objectives of this study were (i) to conduct a LULC change detection analysis; (ii) to undertake a LST change analysis; (iii) to evaluate normalized difference vegetation index (NDVI) calculations to monitor the area of vegetation damage over the study area; (iv) to perform a built-up area calculation analysis using LULC classification and the normalized difference built-up index (NDBI); (v) to conduct vegetation area calculation and damaged area studies using Google Earth and field investigation data from 2010–2020; and (vi) to suggest some implementation strategies for green space development over the study area for a better, healthier life.

The results of this study should be helpful to administrators, local and urban planners and other stakeholders involved in building a sustainable development plan for the Kolkata Municipal Corporation and also for the Howrah Municipal Corporation area, including potential applications to similar megacities worldwide.

2. Green Space-Related Challenges

Urban expansion is often the primary reason for vegetation degradation and increases in urban thermal variations [39]. Figure 1 is clearly show that vegetation areas were cut down to accommodate urban expansion and other anthropogenic activities in the study area. An increase in transportation systems and public vehicles were the main reason for urban expansion and vegetation degradation. Mature trees were removed, and new trees were
planted near the main roads and housing complexes during the period of 2010–2020. The local climate was negatively affected in the study area because of enhanced transportation systems, anthropogenic activities and urban developments. The temperature was also increased during the master area planning time. Vegetation degradation, removal and cut down were the main reasons for air pollution and heat variations during the summer. Shadows created by vegetation help people by providing relief from direct solar thermal heating during the summer (Figure 1).

![Figure 1](image_url)

**Figure 1.** Vegetation degradation area identification on satellite images in 2010 and 2020 for West Bengal (Kolkata and Howrah).

The main traffic problems occurred in the studied cities due to motorbikes and buses, increasing air pollution and aerosols in the air, leading to higher public health risks. Vegetation cut downs in parks and gardens, aimed at enhancing transportation, were greatest in Dharmotala, Howrah, Diamond Harbour Road and Strand Road. Areas including Elite Park, Millennium Park, Princep Ghat, Babughat Park, Royal Calcutta Golf Club and Botanical Garden benefit from parkland, which is characterized by minimal temperature variations during the summer. Temperature variations are associated with increased climate change, environmental degradation and ecological change. Local climates are also affected by anthropogenic activities and vegetation degradation. Soil moisture loss, soil erosion, temperature variation, urban heat stress and land transformation are the main consequences linked to vegetation degradation and built-up area expansion concerning Kolkata and Howrah.

3. Materials and Methods

3.1. Study Region

The capital of West Bengal is Kolkata; this city is the third largest city economy in India. After Kolkata, Howrah is the next fastest developing city in West Bengal. Kolkata is the seventh most inhabited city in India as per the 2011 Indian census. The Kolkata port remains the only and oldest riverine port in India. Kolkata is often acknowledged as the “City of Joy” and the towns of Kolkata and Howrah are known as the “Twin Cities of West Bengal,” India. Both cities are located on the eastern side of the Hooghly River, around 80 km west of the Bangladesh border. Howrah Municipal Corporation
covers 63.55 square kilometers and has a population of about 1,077,000 people, making it Asia’s largest urban town. It contains 38 municipalities, 77 non-municipal urban towns, 16 suburban regions and 445 rural areas. Howrah Municipal Corporation has a population density of 17,000 people per square kilometer (Census of India from 2011). This study area covers a total of 24,168 hectares. The average mean sea level (MSL) in Kolkata and Howrah is between 1.5 and 11 m and the annual average temperature in both cities is 26.5 °C (https://mausam.imd.gov.in/kolkata/, access date: 18 May 2020). The annual rainfall is around 1600 mm (https://mausam.imd.gov.in/kolkata/mcdata/local.pdf, access date: 13 May 2020), with the monsoon month of August being associated with the most rain (Figure 1). The study indicates that the temperate of Kolkata city is commonly between 33 and 36 °C during the summer. In the winter, the annual daily low temperature usually varies between 24 and 33 °C [49].

The main reason for the temperature variation and the climate change impacts on the Kolkata agglomeration is the rapid population pressure, vegetation damage, groundwater shortage, transportation development and industrial work [50]. Both Kolkata and Howrah are located within the Kolkata agglomeration where rapid urbanization influences the local climatic conditions (Figure 2). The most crucial contributors to temperature changes in Kolkata, Howrah and the neighboring urban areas are industrialization, urbanization, population pressure and public vehicles. Kolkata’s urban area is quickly expanding and residents from nearby rural areas have come to the city for a variety of reasons, including job opportunities, transportation, vehicle access and healthcare. Because of population pressure, industrialization and urbanization, many municipalities have developed rapidly near Kolkata, such as Dum Dum, Naihat, Madhayamgram, Maheshtala, Barrackpore, Budge Budge, Bidannagar, Barasat, Rajpur-Sonarpur, Uluberia in Howrah, Hooghly, North 24 Parganas and South 24 Parganas. Kolkata is most affected by climate change because of urban expansion. However, technological developments have also contributed significantly to pollutant levels and have become a major source of air pollution.
Figure 2. Locational map of the study area showing the twin cities of West Bengal (Kolkata and Howrah).

3.2. Data Used

LULC alteration or dynamics were analysis and monitoring using Landsat Thematic Mapper (TM) and OLI/TIRS images. Moreover, 2010- and 2020-year imageries were used to identify an authentic transformation scenario for the earth surfaces of Kolkata and Howrah city, West Bengal, India (https://earthexplorer.usgs.gov/, access date: 13 May 2020) with a minimum cloud cover of < 10%. The 2010- and 2020-year images were taken for LULC,
LST and urban green space change scenario detection. In order to understand the LST and green space developments of this area better, the last data set from 2020 was used as the final data for the study area.

Table 1 shows details of two earth observation datasets. The population data, administrative boundary and the entire Kolkata and Howrah region was derived from the Indian census data (https://censusindia.gov.in/, access date: 7 May 2020). The population data were acquired from the Census Department of India for 2011 and were used for surface urban heat stress mapping purposes. Google Earth data and the field investigation data were also used for the validation of these results. A total of 160 sample points were collected for validation purposes whereas 75% and 25% were used for training and testing purposes, respectively. Supervised classification and maximum likelihood algorithms were applied to classify the earth observation data and also to delineate the LULC change dynamics monitoring in the study area (Figure 3).

Table 1. Details of the satellite data and acquisition date.

| Satellite  | Sensor    | Date         | Path and Row | Data Source                                                                 |
|-----------|-----------|--------------|--------------|-----------------------------------------------------------------------------|
| Landsat 5 | TM        | 2 April 2010 | 139, 44      | https://earthexplorer.usgs.gov/ (accessed on 13 May 2020).                  |
| Landsat 8 | OLI/TIRS  | 28 March 2020| 139, 44      |                                                                             |

Figure 3. Adopted methodology of this study.
3.3. Satellite Image Classification

The RS satellite data were pre-processed to distinguish the LULC transformation and to generalize water bodies, parks, grassland, trees and other vegetation of the study area from 2010 to 2020. To identify patterns with greater accuracy, the earth observation data with minimal alterations were downloaded from 2010 to 2020. To improve remote sensing data, histogram equalization was used [51]. Image rectification or geo-reference is essential to minimize image misrepresentation. To remove image distortion, RS satellite datasets were rectified to fit into the World Geodetic System (WGS) 1984 and the Universal Transverse Mercator (UTM) system with 45 N zones. The FLAASH method was used for the pre-processing of the two Landsat 5 TM and 8 OLI/TIRS data in ENVI software v5.2. ERDAS IMAGINE version 14 was used for image pre-processing and ArcGIS v10.5 was applied for geo-reference, atmospheric and radiometric corrections as well as for last clipping or subsisting area of interest (AOI) on notified software. ERDAS IMAGINE v14 software was used for change detection analysis of the classified imageries. Change detection techniques were widely used to assess land alteration on the earth’s surface. The pixel-by-pixel basis technique was used to monitor land alteration after a new thematic layer was produced using different LULC classes of the maps, covering an altered mixture of ‘from-to’ change classes [52,53]. Satellite image processing and data analysis were the most important aspects in the identification of the actual change in the earth’s surface where urban expansion and population pressure were the main reasons for thermal variations in the megacities. Satellite data can also help in delineating the earth’s surface change and assessing the environmental impacts due to anthropogenic activities.

The standard color combination method was utilized to classify the red, blue and green color bands of the two different year satellite imageries. The study area is characterized by increasing population pressure and urbanization, causing food and housing shortages throughout the period of investigation. The dynamics in terms of changes in LULC were calculated throughout the period of 2010 and 2020. The heat stress and thermal variations of the two different years indicate the variations in environmental degradation over the study area. With the maximum likelihood algorithm, a supervised learning classification method was used to classify the LULC maps from 2010 to 2020. Four types of LULC classes were recognized for two different year maps, which include trees, other vegetation, water bodies, other lands, park and grassland. LULC alteration is the main reason for earth surface change.

3.4. Accuracy Assessment and Kappa Coefficient

LC signifies the natural topographies of the earth’s surface that develop over time, such as vegetated area, water bodies and agricultural land. The examination of changes in LULC is also important for defining LULC over time in the study region [54,55]. The natural LC area was affected by population pressure and industrialization, impacting vegetation cover, agricultural land and so on. To conduct multitemporal LULC classification, the supervised classification method with the maximum likelihood algorithm was used by others [56] to categorize the LULC dynamics investigation using different year Landsat TM and OLI/TIRS. The areas in the study region were divided into four categories: water body, other land, park and grassland and tree and vegetation land of the study area from 2010 to 2020. Two different types of green spaces are identified using satellite images like park or grassland and tree or vegetation land. Those classes are mostly important for green space studies and the investigation of the heat stress in Kolkata and Howrah city.

The LULC classification accuracy was improved by using previous studies [57] through the implementation of post-classification. The problem with the use of different years of satellite RS data is the moderate spatial resolution of the Landsat TM and OLI/TIRS mixed pixels [58]. The accuracy assessment was carried out using ERDAS IMAGINE v14 and ArcGIS v10.5. Accuracy evaluation is a method of determining the relationship between the classification results and the aspect of the earth’s surface. To analyze LULC changes, it is critical to differentiate accuracy levels by appropriately classifying different year
The accuracy assessments of the land use and land cover maps were monitored using the ground reference data. The actual results were interpreted after assessing both the overall accuracy (OA) and the kappa coefficient ($k_i$) (Table 2). The overall accuracy (OA) and kappa coefficient ($k_i$) are shown in Equations 1 and 2.

$$OA = \left( \frac{\sum_{i=1}^{k} n_{ij}}{n} \right)$$  \hspace{1cm} (1)

$$K_i = \frac{(\text{Observed accuracy} - \text{Chance accuracy})}{(1 - \text{Chance accuracy})}$$  \hspace{1cm} (2)

where, $n_{ij}$ indicates the diagonal components of the error matrix, $k$ denotes classes in the LULC classification, $n$ signifies the total sample number and $K_i$ represents the kappa coefficient.

### Table 2. Scale of the kappa coefficient and strength of agreement.

| Sl. No. | Value of K | Strength of Agreement |
|---------|------------|-----------------------|
| 1       | <0.20      | Poor                  |
| 2       | 0.21–0.40  | Fair                  |
| 3       | 0.41–0.60  | Moderate              |
| 4       | 0.61–0.80  | Good                  |
| 5       | 0.81–1.00  | Very Good             |

#### 3.5. Land Surface Temperature (LST) Calculation

The provided formulas were used to create the LST maps. The temperature of an area influences the growth of vegetation. The aforementioned equation was used to obtain the spatial-temporal distributions of LST using RS (Landsat 5 TM and 8 OLI/TIRS) Thermal bands for the years 2010–2020. LST data are important for investigations of the climate change impact on the urban and rural areas where population pressure and anthropogenic activities are the main reason for the thermal variation of the earth’s surface. Previous studies also investigated the LST for urban planning and management purposes [56,60–62].

##### 3.5.1. LST for Landsat TM

LST was calculated using the following steps by recalling the concept reported by others [60]. The temperature brightness was estimated by using the two-step process based on the Landsat TM images. The steps are shown below:

- Equation (3) presents the transformation of the digital number to spectral radiance.

$$L = \left( \frac{L_{\text{max}} - L_{\text{min}}}{DN_{\text{max}}} \right) \times \text{Band} + L_{\text{min}}$$  \hspace{1cm} (3)

where $L$ represents the spectral radiance, the $L_{\text{min}}$ value is equal to 1.238 of the spectral radiance of one digital number and the $L_{\text{max}}$ value is equal to 15.6000 of the spectral radiance of 255 digital numbers.

- Equation (4) defines the spectral radiance conversion to temperature in Kelvin.

$$Tb = \frac{K2}{(\frac{K1}{L} + 1)}$$  \hspace{1cm} (4)

where $K1 = 607.76$ as the first calibration constant, $K2 = 1260.56$ as the second calibration constant) and $Tb$ represents the surface temperature in Kelvin.

- The conversion of Kelvin to Celsius [61] is estimated by Equation (5).

$$\text{LST} = Tb - 273.15$$  \hspace{1cm} (5)
3.5.2. LST for Landsat OLI

- The transformation of the digital number (DN) to spectral radiance (L) \([62,63]\) is calculated by Equation (6).

\[
L = \left(\frac{L_{\text{max}} - L_{\text{min}}}{\text{DN}_{\text{max}}}\right) \times \text{Band} + L_{\text{min}} \tag{6}
\]

where \(L\) represents the atmospheric spectral radiance (SR) in Watts/(m\(^2\)*sr*µm), \(L_{\text{max}}\) monitors the maximum spectral radiance (SR) of the digital number value, Band\(_{\text{min}}\) signifies the minimum spectral radiance (SR) of the band and \(\text{DN}_{\text{max}} = Q_{\text{cal max}} - Q_{\text{cal min}}\) characterizes the maximum and minimum alteration of satellite sensor calibration.

- The metadata file is used for the identification of LST, where the thermal (TIRS) band (band 10) data have transformed from SR to BT once the digital number (DN) value is converted to SR \([64]\) (Equation (7)).

\[
BT = \frac{K_2}{\ln\left(\frac{\lambda_{BT}}{K_1}\right) + 1} - 273.15 \tag{7}
\]

where BT = brightness temperature in Celsius and \(K_2\) and \(K_1\) of the satellite datasets represent the band-specific thermal data conversion constants.

- Calculation of NDVI \([37,62]\) (Equation (8)):

\[
\text{NDVI} = \frac{(\text{NIR} - \text{R})}{(\text{NIR} + \text{R})} \tag{8}
\]

where the range varies as follows: \(-1 < \text{NDVI} < +1\).

- Minimum and maximum NDVI values are used for the proportion of vegetation calculated by using reference \([63]\) according to Equation (9).

\[
P_v = \left(\frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}}\right)^2 \tag{9}
\]

- The land surface emissivity (LSE) is calculated based on the proportion of vegetation \((P_v)\) values. The NDVI threshold method NDVITHM applies Equation (10) \([65,66]\).

\[
\text{LSE} = 0.004 \times P_v + 0.986 \tag{10}
\]

- Conversion of LSE Kelvin to Celsius \([36,66]\) is estimated by Equation (11):

\[
\text{LST} = \frac{\text{BT}}{\left\{1 + \left[\frac{\lambda_{\text{BT}}}{\rho}\right] \ln(\text{LSE})\right\}} \tag{11}
\]

where \(\lambda\) is the wavelength of the emitted radiance.

3.6. Spectral Indices

Urban heat islands were studied using the feasibility of the RS-based different spectral indicators. Landsat 5 TM and 8 OLI/TIRS bands were utilized to determine the NDVI and NDBI indices to estimate the vegetation scenario over the study area. Different spectral indices were derived from satellite imageries for different years, delineating the soil condition of the study area. The spectral indicators have been calculated by the notified formula. The spectral indicators are described in the following sections.

3.6.1. Normalized Difference Vegetation Index (NDVI)

One of the most important components of the earth’s LC is vegetation. A healthy vegetation area always aids in the reduction of soil erosion and flooding issues. It also aids
in carbon dioxide and oxygen cycles as well as weather change, which is influenced by vegetation. In India, 33% of the land is covered by vegetation, which is critical for a healthy lifestyle. In the southern sections of Kolkata, the vegetation quality map (NDVI) shows degradation or decreased vegetation. As a multi-spectral RS data tool, the NDVI is used to recognize vegetation, LC categorization, water bodies, open space identification and various forest types. The NDVI is calculated mathematically as a number ranging from −1.0 to + 1.0. For the purpose of NDVI data, water bodies are characterized by negative values (Equation (12)).

\[
\text{NDVI} = \frac{(\text{NIR} - \text{R})}{(\text{NIR} + \text{R})}
\]  

(12)

In Equation (12), NIP represents the near-infrared and R indicates the red band of the satellite image. Landsat TM and OLI/TIRS are used to calculate the damaged vegetation area. Change detection remains the most potent technique in RS for the identification of aerial changes in vegetation to the non-vegetation area and non-vegetation to the vegetation area.

3.6.2. Normalized Difference Built-up Index (NDBI)

The identification of urban areas was determined using the NDBI. In this approach, the Landsat 5 and Landsat 8 OLI/TIRS shortwave infrared (SWIR) region exhibits a higher level of reflectance associated with the near-infrared area. As seen in Equation (13), this built-up index is used mostly in planning land use and built-up areas [57].

\[
\text{NDBI} = \frac{(\text{SWIR} - \text{NIR})}{(\text{SWIR} + \text{NIR})}
\]  

(13)

The NDBI value ranges between −1.0 and +1.0, with the built-up area captured in the positive range of the NDBI.

3.7. Correlation Analysis

The relationship between the land use/cover map and the LST indicates that the built-up and agricultural lands have higher temperatures than the vegetated areas. The correlational data were derived from the ArcGIS “create fishnet” and “extract multi values to point” tools. Thereafter, the data were calculated in MS word with a scatter plot investigation tool. Various classes of LULC exhibit different thermal variations. The water body is cold, while the built-up area is warmer than other land uses. The ArcGIS software was used to estimate the correlation and condition of the studied area for various years.

3.8. The Urban Thermal Field Variance Index (UTFVI)

The impact of SUHI is mostly described using the Urban Thermal Field Variance Index (UTFVI) [67]. Numerous elements such as heat waves, psychometrics, earth surface alteration and illumination intensity influence LST, giving rise to the surface SUHI and UTFVI phenomena [31]. The UTFVI is calculated using Equation (14).

\[
\text{UTFVI} = \frac{T_s + T_{\text{mean}}}{T_{\text{mean}}}
\]  

(14)

where \(T_s\) represents the LST in Kelvin and \(T_{\text{mean}}\) signifies the mean LST in Kelvin. UTFVI can be classified into six categories (none, moderate, intermediate, strong, stronger and strongest) based on the reflected changes in the urban thermal field (Table 3). The SUHI and UTFVI concepts and the ecological assessment index for this study are shown in Table 3.
Table 3. Scale of Urban Thermal Field Variation Index (UTFVI).

| Urban Thermal Field Variation Index | Urban Thermal Island Phenomenon | Ecological Evaluation Index |
|------------------------------------|--------------------------------|-----------------------------|
| <0                                 | None                           | Excellent                   |
| 0–0.005                            | Weak                           | Good                        |
| 0.005–0.010                        | Middle                         | Normal                      |
| 0.010–0.015                        | Strong                         | Bad                         |
| 0.015–0.020                        | Stronger                        | Worse                       |
| >0.020                             | Strongest                       | Worst                       |

3.9. The Surface Urban Heat Island (SUHI)

The study of SUHI is important for urban heat balance assessments [31,41,67–69]. The SUHI map is estimated using Equation (15) to determine the heat variation in Kolkata and the neighboring area:

$$\text{SUHI} = \left( \frac{T_s + T_{\text{mean}}}{\text{STD}} \right)$$

where $T_s$ stands for the LST (K), $T$ represents the mean LST (K) and STD is the standard deviation of the estimated LST map.

Three types of data have been used for SUHI and UTFVI identification like LST Kelvin, LST mean and standard deviation of the different calculated LST values. The LST means of the two images are 298.65 (2010) and 304.29 (2020) and the STDs are 2.59 (2010) and 3.16 (2020), which are calculated in ArcGIS software after LST Kelvin estimation using the “get raster properties (data management)” tool. After that, the “Raster Calculator” was applied for the estimation of SUHI and UTFVI values of different study periods. Therefore, an urban surface thermal variation study is more important for the identification of the variation of urban thermal comfort [18].

3.10. Heat Stress Index Calculation

The heat stress index was calculated using four criteria in the ArcGIS software, where the weighted overlay analysis techniques are used for delineating the heat stress over the study area. The population density (Census of India, 2011), LST variation, LULC and proximity or distance from the green space are used for heat stress identification. Researchers used this formula to calculate the heat stress using some criteria where LST, population, LULC and green space are more important [45]. For the delineation of the heat stress index, the authors used LST derived from Landsat data, urban green space-related data and a population density map. The heat stress index was divided into four categories, which were low, medium, high and very high.

The weighted overlay analysis tool is widely used to delineate the site selection as well as vulnerability estimation. The heat stress index values are more useful for the identification of the affected land and climate change impacts on the earth’s surface. The selected cities’ population data are converted into a 30 × 30 m grid [70,71] because the Landsat images are of a 30-m resolution. LST, LULC and urban green space proximity are used for 1 km differences. The distance from green space is more important for heat stress identification. All four criteria used for the heat stress index identification are converted for the same geometry. The distance from green space is the main criterion, followed by LST, population pressure and other LULC classes. All criteria are given the same weights for calculating the heat stress index for the Kolkata and Howrah Municipal Corporation. Figure 4 indicates the overall methodology for calculating the heat stress index based on the abovementioned literature review. The “Reclassification” tool in ArcGIS is used for the weighted-based different area estimation. After that, the four criteria maps are taken for the overlay analysis. The heat stress index is divided into four classes: low, medium, high and
very high. For low green and densely populated areas, high temperatures were recorded. In contrast, for dense green space and low population density areas, low temperatures of the earth’s surface were noted.

The kappa coefficients were 0.915 (2010) and 0.907 (2020) (Tables 5 and 6). Two hundred random points were given for accuracy assessment generation using Google Earth and field survey data. Random checking points were selected for land use and land use classification. The accuracy of the vegetation areas was retrieved from the NDVI maps, Google Earth and field survey data.

4. Results and Discussion

The most urban green spaces were identified for the year 2010, but after that, building construction and other urban amenities decreased the vegetated area (Table 4). The accuracy assessment of two different year images were 94% and 93.50% (2010 and 2020), respectively. The kappa coefficients were 0.915 (2010) and 0.907 (2020) (Tables 5 and 6). Two hundred random points were given for accuracy assessment generation using Google Earth and field investigation data.

Table 4. Real land use and land cover changes within the study area.

| LULC Class            | Area (Hectares) | Area (Percentage) | Areal Change (%) |
|-----------------------|-----------------|-------------------|------------------|
|                       | 2010            | 2020              | 2010             | 2020             | (2010 to 2020) |
| Water Body            | 2542.24         | 2198.75           | 10.52            | 9.10             | −1.42          |
| Other Land            | 12743.95        | 15458.34          | 52.73            | 63.96            | 11.23          |
| Park and Grassland    | 2532.89         | 2245.35           | 10.48            | 9.29             | −1.19          |
| Tree and Vegetation   | 6348.64         | 4265.28           | 26.27            | 17.65            | −8.62          |
| Total                 | 24167.72        | 24167.72          | 100.00           | 100.00           |               |

Figure 4. Adopted methodology for heat stress index calculation.

3.11. Validation of the Study Results

The urban green space degradation study used two different year’s satellite images (2010 and 2020) for the Kolkata and Howrah Municipal Corporation area. The most populated area of West Bengal is linked to decreased urban green space and increased urban vulnerability. Thermal variation, heat stress, vegetation deficiency, oxygen demand, climate change and many other variables increased due to vegetation degradation and urban expansion of the study area. The results for urban green space were validated using Google Earth data and field survey data. Random checking points were selected for land use and land use classification. The accuracy of the vegetation areas was retrieved from the NDVI maps, Google Earth and field survey data.
### Table 5. Accuracy assessment and kappa coefficients for the year of 2010.

| Class Name                  | Ground Truth/Reference | Row Total | Commission Error | User Accuracy |
|-----------------------------|------------------------|-----------|------------------|---------------|
| Water Body                  | 28                     | 1         | 1                | 0             | 30            | 6.67%       | 93.33%       |
| Other Land                  | 1                      | 71        | 3                | 1             | 75            | 6.67%       | 94.67%       |
| Park and Grassland          | 0                      | 0         | 27               | 2             | 29            | 6.90%       | 93.10%       |
| Tree and Vegetation Land    | 0                      | 1         | 3                | 62            | 66            | 6.06%       | 93.94%       |
| Column Total                | 29                     | 73        | 34               | 65            | 200           |             |              |
| Omission Error              | 3.45%                  | 2.74%     | 20.59%           | 4.62%         |               |             |              |
| Produced Accuracy           | 96.55%                 | 97.26%    | 79.41%           | 95.38%        |               |             |              |
| Overall Accuracy            | 94.00%                 |           |                  |               |               | Kappa       | 0.915        |

### Table 6. Accuracy assessment and kappa coefficients for the year of 2020.

| Class Name                  | Ground Truth/Reference | Row Total | Commission Error | User Accuracy |
|-----------------------------|------------------------|-----------|------------------|---------------|
| Water Body                  | 25                     | 1         | 1                | 1             | 28            | 10.71%      | 89.29%       |
| Other Land                  | 1                      | 76        | 3                | 2             | 82            | 7.32%       | 92.68%       |
| Park and Grassland          | 0                      | 0         | 27               | 1             | 28            | 3.57%       | 96.43%       |
| Tree and Vegetation Land    | 0                      | 1         | 2                | 59            | 62            | 4.84%       | 95.16%       |
| Column Total                | 26                     | 78        | 33               | 63            | 200           |             |              |
| Omission Error              | 3.85%                  | 2.56%     | 18.18%           | 6.35%         |               |             |              |
| Produced Accuracy           | 96.15%                 | 97.44%    | 81.82%           | 93.65%        |               |             |              |
| Overall Accuracy            | 93.50%                 |           |                  |               |               | Kappa       | 0.907        |

### 4.1. LULC Dynamics

The study area’s vegetated land was noticeably reduced over 10 years. Progressively, the built-up land increased due to urban expansion. The green space was mostly affected by the land transformation and overwhelming population pressure. Flats, shopping malls, roads and many other urban amenities influence the local environment. The anthropogenic activates are greatly affected by the LULC classes. Land values and the quality of land change frequently. The LULC change noticed a significant development because of urban expansion. The water body areas were reduced due to urban planning by 1.42% (Table 4). Other lands were classified as built-up, commercial, industrial and road network lands (Figure 5). Around 11.23% of the area has been converted into other lands due to anthropogenic activities. The tree and grass LC area has decreased; around 1.19% of grassland and 8.62% of tree cover area decreased due to overwhelming population pressure and building construction work (Figure 6).
Figure 5. Land use and land cover (LULC) classification in 2010 and 2020 in West Bengal (Kolkata and Howrah).

Figure 6. LULC change analysis using a bar diagram for 2010 and 2020 concerning West Bengal (Kolkata and Howrah).
4.2. Spatial Distribution of LST

Industrial works, transportation development, urban expansion and a huge amount of consumed fossil fuel are the main reasons for climate change along with thermal variation over the earth’s surface. Therefore, LST estimation is more important for the investigation of the impact of climate change on the urban environment. The maximum temperature is indicated by red color on the map, while the lowest temperature is indicated by blue color. The LST increased by its highest value of 2.99 °C during 2010–2020 (Figure 7). The annual average LST was 0.299 °C (2010–2020). The highest temperature shows those central and northern parts in the year 2010. The highest temperature was 30.02 °C and the lowest was 16.56 °C. The entire area was linked to low temperatures in the year 2010, but after that, the temperature increased due to anthropogenic activities and natural extreme events. By the year 2020, most parts were located in a high temperate zone. In the year 2020, the central, northern and eastern parts were mostly characterized by a temperate zone. The highest temperature was 33.01 °C and the lowest 22.00 °C in the year 2020. Built-up land and many human-caused activities were the explanation for temperature variations in Kolkata and Howrah, West Bengal, India.

![Figure 7. The LST variation over the years 2010 and 2020 for West Bengal (Kolkata and Howrah).](image)

4.3. Spectral Indices

The NDVI was high in the year 2010 but after that, the NDVI values decreased. The highest NDVI value was 0.53 and the lowest value was −0.33 in the year 2010 (Figure 8). The NDVI values were highest (0.44) and lowest (−0.14) in 2020. Many parts of this area were facing a huge amount of vegetation degradation and increases in built-up land over the study area. Vegetation-damaged areas are located in the southwest, east, northwest and central parts of the study area. Central and northern parts of the study region were already densely built up. Therefore, the built-up area expansion was linked to the southern parts, where the vegetation areas decreased. This influences the urban heat island effect and ecological conditions over the study area. The NDBI maps of the study area showed considerable variation (Figure 9). The values of NDBI were 0.29 (highest) and −0.34 (lowest) but after ten years, the NDBI values were 0.46 (highest) and −0.53 (lowest). The NDVI and NDBI indices show that the built-up land increased, and the vegetation area decreased due to anthropogenic activities. A vegetation and urban expansion analysis is more important
for investigating the green space dynamics and built-up expansion over the study area where vegetation areas decrease, and urban areas increase.

**Figure 8.** Normalized difference vegetation index (NDVI) variations in 2010 and 2020 for West Bengal (Kolkata and Howrah).

**Figure 9.** Normalized difference built-up index (NDBI) variation in 2010 and 2020 for West Bengal (Kolkata and Howrah).

4.4. Correlation Analysis Using LST and Spectral Indices

The NDVI and NDBI indices were used to estimate the correlation with LST. The correlation between LST and NDVI shows a significant change. The $R^2$ values varied
between 0.48 (2010) and 0.23 (2020), respectively. The correlation between LST and NDBI shows important levels of change. The $R^2$ values varied between 0.38 (2010) and 0.61 (2020), respectively (Figure 10).

Figure 10. Correlation analysis between LST and spectral indices.
4.5. Urban Green Space Patterns

The classification results show the vegetation cover change areas in the different time periods over the study area. The results indicate that some of the vegetation areas were transformed into built-up areas and other urban amenities. Vegetation areas have the potential to improve health, but overwhelming population growth damaged the vegetated areas due to urban expansion. The central parts, northern, northeastern and many areas of the northwestern parts became densely populated within the last ten years. Grassland and tree-covered areas have been converted into urban amenities.

The urban green space area was significantly changed due to urban expansion (Figure 11). The green space change maps clearly show that the grassland and tree-covered areas were huge in the past, but their size was subsequently reduced due to anthropogenic activities and urban expansion. The road site tree and grasslands were vastly converted into built-up land. Therefore, implementation strategies are needed for introducing heat variation during the summer over the study area. Planting trees (e.g., roadside tree plantations) and rooftop tree plantations are suitable to decrease heat stress over the study area and maintain previous oxygen levels.

![Green space dynamics in 2010 and 2020 for West Bengal (Kolkata and Howrah).](image)

Figure 11. Green space dynamics in 2010 and 2020 for West Bengal (Kolkata and Howrah).

The limitation of the classification results are high resolution and atmospheric conditions. Nevertheless, the classification results show very significant aspects for delineating the urban green space condition over the study area. Remote sensing data were widely used for mapping and monitoring purposes for different urban works (Figure 12). This study is also helpful for planning purposes.

Urban green space studies are important for investigations of urban expansion and related problems like air pollution, traffic congestion, soil erosion, oxygen deficiency and precipitation-related fluctuations. Kolkata and Howrah are the two cities where the vegetation parts are mostly depredated due to built-up expansion, population pressure, infrastructural development and other urban amenities. Figures 11 and 12 indicate the green space variation in the Kolkata and Howrah Municipal Corporation. Behala, Thakurpukur and Tollygunje as well as some parts of Khidirpur lost huge areas of green space in Kolkata. Southern and southeastern parts of the Howrah Municipal Corporation also noticed huge green space losses from 2010 to 2020. Those scenarios are devastating and proper planning, adaptation policies and awareness-raising activities are needed to protect the environment.
which indicate that the urban heat effects increase gradually due to population pressure. The SUHI effect can also be seen on the map of the UTFVI in Table 3. With urban expansion, the UTFVI index has experienced a significant change in values. The investigated areas have been turned into urban areas in recent decades. The riverine areas as well as the southern and eastern regions of Kolkata saw the most construction developments. The central part of the region as well as some industrial areas experience higher urban heat than the remaining areas. For the year 2020, the white to brown color suggests a high SUHI (Figure 13). The SUHI values vary between 3.66 (2010) and 4.79 (2020), which indicate that the urban heat effects increase gradually due to population pressure and anthropogenic activities. The annual average SUHI value increased by around 0.113 during the study period from 2010 to 2020. Smart city planning has become a significant component of future environmental developments. Salt Lake, Newtown and Rajarhat were created as well-planned businesses and residential hubs, but the soil conditions and land subsidence have made some of this area a wetland due to overloaded building contraction. In this situation, the most acceptable course for these cities is afforestation and careful planning. This study raises awareness among those who can help to resolve the situation. The SUHI effect can also be seen on the map of the UTFVI in Table 3. With urban expansion, the UTFVI index has experienced a significant change in values. The investigated areas

Figure 12. Recent zone-wise green space and grassland of West Bengal (Kolkata and Howrah).

4.6. Urban Heat Island Evaluation

Calculating the SUHI is more significant for long-term planning and environmental management. People are often migrating to cities. Also, the recently created municipalities in this research area are Rajpur-Sonarpur, Uluberia, Pujali and Moheshtala, which are rural–urban edge areas that have been turned into urban areas in recent decades.
experienced more thermal field variance from 2010 to 2020 (Figure 14). During those years, an increase of 0.006 in UTFVI was observed due to urbanization.

Figure 13. SUHI variation in 2010 and 2020 for West Bengal (Kolkata and Howrah).

Figure 14. Urban thermal field variation index (UTFVI) variation in 2010 and 2020 for West Bengal (Kolkata and Howrah).

4.7. Heat Stress Index

Urbanization, population pressure and industrial works can increase public health-related problems and health emergencies due to thermal variation and heat stress. In the summer, people can face health-related problems due to heat stress. The risk index indicates
the need for a better design to promote sustainable development over the study area. The very high heat stress is linked to 17.35% of the area. High heat stress is experienced in 35.98% of the area. In comparison, low heat stress has a cover of only 12.65%. The central, northern and southeastern parts are comprised of mainly high heat stress areas. Basically, Kolkata port, Diamond Harbour road, Dharmotala road, Tollygunje and Howrah station area were most affected due to negative thermal variations (Figure 15).

![Figure 15. Heat stress index map of West Bengal (Kolkata and Howrah).](image)

The urban heat stress index shows that the high heat stress area was located in the central, northern and northwestern parts of this area, because of a high rate of building construction and densely built-up lands. The urban heat stress map can provide general information about the thermal variation over the study area. The heat stress index can help administration, local planners, urban planners and other stakeholders to promote sustainable urban health. The heat stress index is high for main roads, areas with large distances from vegetation areas, metro stations and areas where the green spaces were removed for building purposes. Urban expansion and anthropogenic activities are the triggering factors for heat islands and heat stress, whereas vegetation dynamics are the main reason for the SUHI and the heat stress noted over the study area. A high heat stress index indicates the industrial areas like Khidirpur and the heavy transportation areas such
as the central, northern and northwestern parts of the study area. The southern parts of KMC as well as the northern and northeastern parts of the HMC areas are comprised of more vegetated lands. The heat stress index indicates thermal variations and urban expansion-related activities of interest for future planning. The heat stress index is also useful for future disaster planning, management and development of the study area. Most urban areas of West Bengal (State of India) are located in those two cities where traffic congestion and road density play a vital role in thermal variations in the study area.

Urban green spaces have positively affected urban environmental conditions. Green spaces also control local ecological conditions. According to the United Nations 2030 Agenda, the citizens of every area should have universal access to green spaces and a connection between urban and peri-urban areas should be built according to some sustainable development goals. The research highlighted that the urban green space deficiency influences the SUHI and affects the thermal variation over Kolkata and Howrah city, West Bengal, India. Thermal variations also trigger socioeconomical activities, urban ecology developments as well as resilience and green space deficiencies. Green areas are necessary for maintenance, awareness for the building of greenery, rooftop gardening and many other essential works. Green areas contribute to a sustainable water cycle and mitigate climate change and global warming. Administrators, urban planners, policymakers and other stakeholders require proper planning and management guidelines to achieve sustainable development of urban areas like megacities (e.g., Kolkata and the adjacent city Howrah). Good cost-loss planning and governance practices are needed to manage a proper balance between residential and vegetation areas. Due to overwhelming population pressure, urban expansion, industrial works and transportation accessibility, urban areas are deficient of greenspace.

5. Conclusions, Limitations and Further Research Proposals

The main focus was on the evaluation of UGS over the twin cities Kolkata and Howrah, West Bengal, India, using Landsat 5 TM and 8 OLI/TIRS during the time intervals of May 2010 and May 2020. The main objective of this study was to find out the physical environmental conditions, LST, urban green space deficiency and development of built-up area. Within three years of this study, the results showed that green spaces decreased. The SUHI and UTFVI maps indicate the variation in thermal conditions and ecological disturbances in both Kolkata and Howrah Municipal Corporation. Huge amounts of green spaces were lost due to urban expansion, population pressure and industrialization.

The study results support management of the monitoring of urban green space and should support human-friendly and healthy urban planning targets. The study results are helpful for administrators, policymakers and urban planners to come up with better planning and management strategies for sustainable urban development and healthy urban living.

The study has several limitations: the satellite images are only of 30-m resolution; residential and vegetation areas are often heterogeneous; and a thermal variation analysis would be more relevant for daily rather than annual data. Nevertheless, it is clear from the findings that environmental degradation increased due to urban expansion. Urban heat stress increased due to densely built-up land. To reduce urban vulnerability, urban green spaces should be increased by planting vegetation along the sides of streets and main roads. Rooftop gardening should also increase the vegetation area in the study region. Indian forest departments and state governments have already started vegetation plantations on the sides of main roads and within central parts of metro stations.

The authors suggest the practical application of the proposed indices by urban planners, local governments and practitioners of various disciplines. As only two indices are mostly used for green space dynamic estimation and built-up expansion investigations, they are also more useful for land alteration analysis in the future. Further research is recommended in the following areas: groundwater shortage, infiltration rates, microclimate studies, site selection for afforestation, land subsidence due to construction as well
as road accidents and the safety of roads. More targeted awareness programs, citizen participation and volunteer actions are also suitable measures to increase vegetation areas and improve the quality of life in urban areas. Smart adaptation and mitigation strategies will be required for urban green space deficiency prevention.

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Agronomy 2022, 12, 2129

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