Technical Note
Understanding the Linkage between Urban Growth and Land Surface Temperature—A Case Study of Bangalore City, India

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Abstract: Planning for a sustainable future involves understanding the past and present problems associated with urban centers. Rapid urbanization has caused significant adverse impacts on the environment and natural resources. In cities, one such impact is the unsettling urban growth, resulting in the urban heat island (UHI) effect, which causes considerable positive feedback in the climate system. It can be assessed by investigating the relationships between urban Land Use/Land Cover (LULC) changes and changes in land surface temperature. This study links the urban transformations in Bangalore, India, between 2001 and 2021, with the city’s changing average land surface temperatures. LULC classification was performed on Landsat satellite images for the years 2001, 2011, and 2021, using the support vector machine (SVM) classification algorithm. LULC change analysis revealed an increase in the built-up area coinciding with a decreasing trend of water bodies, vegetation, and the area under the others (wasteland/open land/barren land) category. The results show that built-up increased from 462.49 km² to 867.73 km², vegetation decreased from 799.4 km² to 485.72 km², and waterbody declined from 34.28 km² to 24.69 km² in 20 years. The impact of urbanization was evident in Bangalore’s land temperature changes between 2001 and 2021, showing the average temperature increased by 0.34 °C per year between the highest UHI events, contrary to 0.14 °C per year in non-urbanized areas. It is hoped that the results of this study can help the urban planners of Bangalore city identify critical areas where improvement in urban dwelling could be planned sustainably according to the global smart cities concept, an offshoot concept of the Sustainable Development Goal (SDG)-11.

Keywords: LULC; change detection; LST; MODIS; Landsat; USGS; Earth Explorer; SDG-11

1. Introduction
Urbanization is the shift of population from rural areas to cities with high population density and built infrastructure [1]. Over half of the human population now lives in cities, and it is estimated that two-thirds of the world’s population will be urban by 2050 [2]. Urbanization is advantageous for human development, and urban productivity is five times more than in rural areas [3]. Better access to infrastructure, including various types of technology, transportation, communication, educational and medical facilities, and better job opportunities are among the common reasons for this urbanization trend. Urbanization in India is at a rapid pace post-independence, as proved by the estimates that the population living in cities in 1901 was 11.4% and has increased by 30% as per the 2011 census in India [4].
Several Indian cities have gone through dramatic urban expansion rates, such as Bombay, Delhi, Calcutta, and Bangalore [5].

However, unmanaged urbanization has deleterious impacts on biophysical and socio-economic systems. The proliferation of urban areas leads to various adverse environmental impacts on natural resources [6]. The transformation of natural resources into settlements is one of the significant impacts of urbanization [7]. The degradation of the water bodies and vegetation replaced by the urban built-ups further aggravates environmental degradation in urban centers. The rising population is another issue faced in the city, which causes a deficiency in basic amenities such as purified water, air, and residence [8]. Urban growth, pollution, and natural resource decline are the adverse impacts of urbanization [9]. Due to these issues, the United Nations constituted 17 sustainable development goals as its sustainable development worldwide agenda for 2030 [6,10].

The sustainable creation of urban centers is one of the sustainable development goals (SDG) goals. Among many, SDG-11 specifically proposes that cities need to be redesigned using sustainability concepts, requiring significant building and management practices [11]. As the cities and their populations’ increase, the expanse of mega-cities also increases, particularly in developing countries such as India [12]. SDG-11 aims to create jobs and housing, improve living standards, safeguard communities, and build economies without impacting the environment and earth system. The goal also calls for significant investment in public transport, open spaces, and management by the citizenry in services and inclusive urban landscapes [13]. However, sustainability cannot be achieved unless the current urbanization trends and their impacts are assessed to direct informed decision making. India, being a signatory of the UN SDGs, has committed to follow SDG-11 in every region of the country [14].

One of the key impacts of urbanization is the proliferation of urban heat islands (UHI). The phenomenon wherein densely populated concrete buildings become hubs of tremendous heat [15]. These hubs are specifically referred to as UHIs. These areas are known to affect the regional climate system that overall acts as additional inputs of heat to the already greenhouse-effect-based warming [16]. As a result, UHIs are partly responsible for the net warming of the planet. Several studies have been conducted on UHI and LULC. Haashemi et al. (2016) examined the seasonal variations of UHI in Tehran, Iran, in relation to a variety of surface biophysical variables. They employed three UHI indicators to quantify its intensity: the LST difference between urban and rural, urban–agriculture, and urban–water. To quantify the link between LST seasonal fluctuation and surface attributes, physical and biophysical surface variables such as LULC, topography, impermeable surface (IS), fraction vegetation cover (FVC), and albedo were chosen. They proposed that in semi-arid cities such as Tehran, where the urban–rural indicator is used, an urban cool island is seen during the day while UHI is shown at night [17]. Hung et al. (2006) used remote sensing to compare UHI in 18 megacities from tropical and temperate climate zones. To create land-surface temperature (LST) maps, they used the least clouded scenes of MODIS obtained between 2001 and 2003. Each city’s UHI trends were studied over the course of its 24 h period and seasonal fluctuations. This research provided a broad overview of the UHI phenomenon in Asia, and the findings were used to guide future research combining satellite thermal data with land-surface modelling and meso-scale climatic modelling to better understand the effects of urbanization on local climates in Asia [18].

The present study was carried out in Bangalore city, Karnataka state of India, and it is one of the five major cities of India. Bangalore city has been expanding rapidly, especially in the last two decades. Bangalore, being the third most highly populated city in India as per the 2011 census, is also the 18th most populated city in the world. Based on the 2001 census, the population in Bangalore’s urban district was 5,759,987, and in 2011 the population increased to 8,749,944, showing an increase of 2,989,957 persons in just ten years, i.e., 51% population growth from 2001 to 2011. As a result, there has been a tremendous increase in the city’s infrastructure development, which has resulted in the formation of UHI events [19,20].
The present study aims to assess the impacts of Bangalore city’s urbanization over 20 years on other essential types of Land Use/Land Cover (LULC) and on the city’s land surface temperatures. For LULC classification and change analysis of Bangalore City, we used the support vector machine (SVM) algorithm to classify Landsat satellite images from 2001, 2011, and 2020. We also evaluated the average increase in the land surface temperature of Bangalore city during this period using MODIS satellite data [21]. This study particularly focuses on the relationship between urban growth and UHI events during the April months from 2001 to 2021. Climatologically, April is considered to be the hottest month in Bangalore.

2. Study Area

Bangalore is the principal administrative, commercial, cultural, industrial, and knowledge capital of the state of Karnataka. Bangalore is in southern India on the Deccan plateau at 914 m above sea level. It is one of the biggest cities in India and is also designated as the Capital IT City of India, referred to as the Silicon Valley of India. One of the significant advantages of Bangalore is its climate. The climate of Bangalore is moderate, with the highest temperatures ranging from 35°C to 38°C in April/May. As per the Koppen Classification, Bangalore has a Tropical Savanna Climate (Aw). The summer season lasts from April to June, as per the Bangalore environment. The minimum temperature during winter is also very moderate, around 10°C. The winter season is from December to February. The monsoon season starts from June and extends up to September, and it is noticed that 85% of rainfall occurs in evening times only [22]. Figure 1 shows the location of Bangalore with respect to the state of Karnataka and India.

![Figure 1](image-url)
3. Methodology

3.1. Land Use and Land Cover Classification

We used Landsat images of three different dates from USGS Earth Explorer (United States Geological Survey) for LULC classification. For LULC classification, the dates chosen were 2001, 2011, and 2021. The details of all the datasets used in this study are provided in Table 1.

Table 1. Details of the datasets used in this study.

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Path</th>
<th>Row</th>
<th>Date of Acquisition/Temporal Resolution</th>
<th>Satellite</th>
<th>Spatial Resolution</th>
</tr>
</thead>
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<td>1</td>
<td>144</td>
<td>51</td>
<td>3 April 2021</td>
<td>Landsat-5 (TM) (Bands 1–5, and 7)</td>
<td>30 m</td>
</tr>
<tr>
<td>2</td>
<td>144</td>
<td>51</td>
<td>7 March 2011</td>
<td>Landsat-5 (TM) (Bands 1–5, and 7)</td>
<td>30 m</td>
</tr>
<tr>
<td>3</td>
<td>144</td>
<td>51</td>
<td>27 March 2001</td>
<td>Landsat-8 (OLI) (Bands 1–8)</td>
<td>30 m</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>-</td>
<td>8-day avg. april 2001 till 2021 (UHI events, max T)</td>
<td>MODIS (11 A2)</td>
<td>1000 m</td>
</tr>
</tbody>
</table>

The dates of the Landsat images were selected as close as possible to the land surface data of the MODIS as shown in Table 1. The Landsat satellite images for 2001, 2011, and 2021 were classified into Built-up, Water, Vegetation, and Others categories. For each LULC class, 100 training samples for each chosen class were collected to classify the Landsat images using the support vector machine (SVM) classification method in ArcGIS version 10.4.1. It is best for segmented raster input, but it also works with standard imagery. It is a classification system algorithm that is widely utilized in research. The tool handles multiband imagery for any bit depth for conventional image inputs, and it performs classification on a pixel-by-pixel basis based on using the input training samples. The attributes are computed in order to create a classifier definition file that can be utilized in another classification program as well. In ArcGIS, the training samples manager is used to acquire the training sample data many times. While choosing the best samples for classifying the images into the above LULC types, various image enhancement techniques were used in addition to field-based knowledge, such as filtering and histogram matching [23]. These helped to select the best samples for classification. SVM is based on the statistical theory used for the classification and regression problems of urban centers worldwide [24], hence it was used in the present study. Moreover, the SVM classifier has various advantages over the maximum likelihood classification (MLC) approach, including the need for fewer samples and the absence of a normal distribution requirement. Noise, linked bands, and unequal numbers or quantity of training areas within each class are also less of a concern [25]. We classified Bangalore into four generalized LULC classes, Built-up, Vegetation, Water, and Bare land, and conducted a LULC change analysis from 2001 to 2021 to understand how Bangalore and its surroundings changed during this period. The classification criteria for these chosen classes were based on this work’s predefined objectives, i.e., to understand the role of changing built-up and vegetation on the land surface temperature of Bangalore. The category Others included the Bare land, Wasteland, and Open land classes. It has been observed that this LULC category finally becomes converted into infrastructure and built-up, as evidenced by the change detection observations concluded from the present study. Accuracy assessment is a crucial aspect of defining the quality of LULC maps. We performed the accuracy assessment of the LULC for 2021 using the field-based ground-truthing. For 2011 and 2001, we used Google Earth historical imagery. The accuracy was assessed using the user’s accuracy (manual
classification accuracy), producer’s accuracy, SVM classification accuracy and the kappa coefficient. The kappa coefficient \( k \) is mathematically expressed as [25–28]:

\[
k = \frac{N \sum_{i=1}^{r} (X_{ii}) - N \sum_{i=1}^{r} (X_{i+} X_{+i})}{N^2 - \sum_{i=1}^{r} (X_{i+} X_{+i})}
\]

where \( r \) represents no. of rows in the error matrix; \( X_{ii} \) represents no. of observations in row \( i \) and column \( i \); \( X_{i+} \) is the total of observations in row \( i \); \( X_{+i} \) is the total of observations in the column \( i \); and \( N \) is the total number of observations included in the matrix.

3.2. Land Surface Temperature (MODIS) and LULC

For evaluating the land surface temperature change between 2001 and 2021, we used MODIS 11A2 product, downloaded from the NASA-Earth Data repository. Land surface temperature assessment helps to assess the temperature change that comes along with urban change [29–32]. The MODIS LST product has a 1 km spatial resolution. The change in the LST in 2001, 2011, and 2021 is evident, as discussed in the Section 4 below. We selected ten well-known areas within the urban cluster and used ground surveys to ensure that each had been built up since 2001. For each of these ten sites, we screened 8-day average MODIS LST data obtained during the month of April from 2001 to 2021. The 8-day window within each of these April periods that had the highest LST value was extracted and used in analyses to determine the rate of change in LST across the 21-year study period [33]. A Python script was prepared to convert the downloaded HDF files to TIFF format and reproject the converted TIFF images to the WGS UTM coordinate system. Moreover, a separate python script was prepared to extract the numerical LST data from daily MODIS LST images for the study region and to get 8-day average LST daily for the month of April from 2001 to 2021. Furthermore, to nullify the influence of the local weather or climatic change and ascertain whether the increase observed in the LST is a result of urban expansion only, we carried out field visits to Bangalore’s outskirts and selected ten non-built-up sites where LULC has not changed since 2001. These locations have been open land since 2001 and are still the same. The sites were selected in a way that within the radius of 500 m, the LULC has remained the same since 2001, so that it matches the spatial resolution of the MODIS LST (1 km), and the temperature value of the land parcel associated with LULC can be compared. The same process of extracting the 8-day LST data that had the maximum LST value was carried out for non-urbanized areas as well. The available LST data in Hdf format was initially projected and then converted into TIFF format along with the generation of the raster attribute table. The equation used to convert the pixel values of MODIS to Degree Celsius is [34],

\[
\text{"[Value] } \times 0.02 - 273.15"
\]

The output images were exported and analyzed for comparison. Figure 2 shows the overall methodology utilized in this study.
In order to understand the trends in the changing temperature of the UHI events at built-up and non-built-up sites from 2001 to 2021, we performed a trend analysis for all the sites. The physical significance of this analysis lies in the fact that the results depicted whether or not the processes governing the temperature increase at the same site between the two dates are the same or not. In the present case, built-up expansion is the process that is hypothesized to be governing the LST increase and the corresponding UHI event at the observation sites.

4. Results and Discussion

4.1. Land Use and Land Cover Change Analysis

These results of LULC change in Bangalore for 2001, 2011, and 2021 are shown in Figure 3a–c, respectively. For 2021, we performed ground-truthing, whereas, for 2011
and 2001, we collected several sample reference points from high-resolution Google Earth historical imagery and compared that with the mapped LULC each year. We performed stratified random sampling to collect the reference points. Based on the derived confusion matrices, the overall accuracy of the LULC classification of 2021, 2011, and 2001 was 96.32%, 94.12%, and 93.65%, respectively. The various other accuracy indices are shown in Table 2.


<table>
<thead>
<tr>
<th>SVM Classified LULC Categories</th>
<th>Manually Classified LULC Categories</th>
<th>SVM classification accuracy</th>
<th>Grand Total</th>
<th>Manual classification accuracy</th>
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<td>BU</td>
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<td>Total</td>
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<td>96.67%</td>
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<td>100.00%</td>
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<td></td>
<td>Grand Total</td>
<td>34 31 33 38</td>
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<td></td>
<td>SVM classification accuracy</td>
<td>97% 100% 88% 100%</td>
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<tr>
<td></td>
<td>Total Correct 131; Total Samples 136; Overall Accuracy 96.32; Kappa Statistic 0.91</td>
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</tbody>
</table>

Error Matrix of LULC from LANDSAT OLI 2021 Using Google Historical Imagery

<table>
<thead>
<tr>
<th>SVM Classified LULC Categories</th>
<th>Manually Classified LULC Categories</th>
<th>SVM classification accuracy</th>
<th>Grand Total</th>
<th>Manual classification accuracy</th>
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<td>Grand Total</td>
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<td></td>
<td>SVM classification accuracy</td>
<td>100% 94% 88% 95%</td>
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<tr>
<td></td>
<td>Total Correct 128; Total Samples 136; Overall Accuracy 94.12; Kappa Statistic 0.9</td>
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Error Matrix of LULC from LANDSAT TM 2001 (C2-L1) using Google Historical Imagery

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<thead>
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<th>SVM Classified LULC Categories</th>
<th>Manually Classified LULC Categories</th>
<th>SVM classification accuracy</th>
<th>Grand Total</th>
<th>Manual classification accuracy</th>
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<tr>
<td></td>
<td>BU</td>
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<td>1 1 1</td>
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<td>85.71%</td>
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<td>SVM classification accuracy</td>
<td>97% 91% 85% 97%</td>
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Figure 3. Cont.
Figure 3. Land use and land cover SVM classifier, (a) 2021, (b) 2011, and (c) 2021.

In 2001, the built-up area was covered by 21.16% of the total Bangalore area of 462.49 km². In 2011, urban areas increased to 553.40 km², which is 25.32% of the total area. The total built-up area reached 867.73 km² in 2020, 39.70% of the entire Bangalore city. We can see a sudden increasing trend of urban built-up areas from 2001 to 2021, 87.62% growth in just 20 years. Figure 4 shows the built-up changes by 2001, 2011, and 2021.

Figure 4. Column graph showing comparative vegetation change for 2001, 2011, and 2021.

The study also identified that the waterbody covered 34.28 km² in 2001. In 2011, the waterbody area had declined to 30.42 km², and it decreased again to 24.69 km² in 2021. Water bodies show an entirely decreasing trend with increasing urbanization. Figure 6 shows the trend in the waterbody decrease in the study area.

Figure 5. Column graph showing comparative vegetation change for 2001, 2011, and 2021.
We observed a decrease in a vast vegetation area in just 20 years by evaluating vegetation trend changes. In 2001, the vegetation-covered area was 799.4 km$^2$, which turned to 601.90 km$^2$ in 2011. In 2021, the vegetation area decreased to 485.72 km$^2$. We found a total reduction of 313.68 km$^2$ of vegetation area in 20 years. Figure 5 shows the trend in vegetation change.

The study also identified that the waterbody covered 34.28 km$^2$ in 2001. In 2011, the waterbody area had declined to 30.42 km$^2$, and it decreased again to 24.69 km$^2$ in 2021. Water bodies show an entirely decreasing trend with increasing urbanization. Figure 6 shows the trend in the waterbody decrease in the study area.
The Others category includes barren land, open land, wasteland and fallow land. We observed a slight change in the areas under this category. In 2001, it was covered by 888.89 km$^2$, and in 2011, it slightly increased to 999.38 km$^2$, and it decreased again by an area of 806.96 km$^2$. Figure 7 shows the trend change in area under barren land in 20 years.

Figure 7. Column graph showing comparative change in Others category for 2001, 2011, and 2021.

4.2. Land Surface Temperature Assessment

We selected 20 well-distributed reference pixels of MODIS LST, 10 from the built-up and 10 from the non-built-up areas. These pixels pertained to those sites that have not changed in the LULC since 2001 for assessing the relationship between changing surface temperature and LULC. All the selected locations showed increasing trends in temperature from 2001 to 2021. We selected the month of April for assessing the change in temperature from 2001 to 2021 owing to the fact that the month of April is the hottest in Bangalore, and we aimed to understand what has happened to the hottest month of the year. Here, it is also notable to mention that the annual average temperature of MODIS for 2001, 2011, and 2021 did not show any significant changes. Hence, the hottest month was selected for the assessment. We analyzed the trends of LST in the selected urban and non-urban locations and found that some of the urban locations show increasing trends in LST. Figure 8 shows the LST trends in the selected ten urban areas. It was observed that the highest temperature events (UHI events) throughout all the Aprils between 2001 and 2021 showed increasing trends. This provides an excellent insight into the underlying processes that are operating similarly in all the events.

The areas surrounding non-urban areas have witnessed increased LST due to the conversion of vegetation into built-up, the exact non-urban sites are still not showing much temperature rise (Figure 9). This clearly indicates the impact of urbanization on the temperatures of Bangalore because the main process operating in the background for raising the temperature of the urban areas is concretization and infrastructure development.
Figure 8. Trend analysis of the UHI events of the selected urban locations (UL) in the month of April from 2001 to 2021. UL1 Hegganahalli, UL2 Kurubarahalli, UL3 Malleswaram, UL4 Banashankari, UL5 Electronic City, UL6 Jayanagar, UL7 Indiranagar, UL8 Koramangala, UL9 Hebbal, and UL10 Gandhi Nagar.
Figure 9. Trend analysis of the UHI events of the selected ten non-urban locations (NUL) in the month of April from 2001 to 2021.
Moreover, in order to understand the impact of urbanization on the temperature at two sets of sites, we modeled LST (considering it as a dependent variable) as a function of the year, locations, and LULC type. We used the following linear mixed-effect model form to understand this relationship:

$$\text{LST} \sim \text{Urbanization} + \text{Year} + \text{Urbanization: Year} + (1|\text{Site})$$

It was observed that the mean-modeled LST as a function of the above parameters shows an increasing trend with a slope of 0.247 °C per year in contrast to 0.056 °C per year in non-urbanized areas. This, to some extent, provides some inferences that urbanization governs the increasing LST at the observational sites. Figure 10 shows the rate of change in LST between the two types of sites across the study period based on the significance of the interaction of governing factors.

![Regression lines for modeled mean LST](image)

**Figure 10.** Modeled mean LST as a function of the interaction of time, location, and LULC calculated using linear mixed-effect model. LULC-1: urban locations; LULC-2: non-urban locations.

In order to understand the relationship between the LULC of 2001, 2011, and 2021, we plotted the UHI events of the month of April for these years, as shown in Figure 11. By comparing the temperature change of 10 urban locations and calculating the mean value, we observed that around these observational urban sites there had been increase in the LST corresponding to increase in urbanization. Figures 12 and 13, show the land surface temperature of the UHI event bar diagram for April 2001, 2011, and 2021 in ten urban and non-urban sites, respectively. The Y-axis shows temperature values in °C.
Figure 11. Urban heat island events of April (a) 2001, (b) 2011, and (c) 2021. Green triangle symbols are the urban and blue ones are the non-urban observation sites.

Figure 12. Land surface temperature assessment bar diagram of ten field reference locations of urbanized areas.
Since we have compared the temperature changes in the urbanized and the non-urbanized locations, the higher temperature increases in the urbanized areas compared with the non-urbanized support the influence of the urban clusters in increasing LST. The areas surrounding the non-urbanized areas in our study have also shown an increase in average LST during the UHI events, similar to the results reported by Govind and Ramesh (2019) and Siddiqui et al. (2021). One more important observation from our study is the decreasing vegetation and increasing built-up surrounding the non-urbanized areas.

We analyzed the relationship between temperature ranges for the three dates (2001, 2011, and 2021), i.e., >32.68, 32.68–34.67, 34.68–36.67, 36.68–38.67, and <38.67 and the corresponding land surface area in each range, and it was observed that there had been an increase in the areas with higher temperatures during such UHI events. The areas under the lower T range are decreasing, and the areas under the higher T range are increasing, as depicted in the graph below (Figure 14). Overall, Bangalore witnessed an increase in the average LST of the UHI events in the month of April.
Now, since we have compared the temperature changes in the urbanized and the non-urbanized locations, the higher temperature increases in the urbanized areas compared with the non-urbanized support the influence of the urban clusters in increasing LST. The areas surrounding the non-urbanized areas in our study have also shown an increase in average LST during the UHI events, similar to the results reported by Govind and Ramesh (2019) and Siddiqi et al. (2021) [20,35,36]. One more important observation from our study is the decreasing vegetation and increasing built-up surrounding the non-urbanized locations. The increase in the temperature as such could be well-attributed to the increasing built-up and decreasing vegetation, as indicated in Figure 3.

This findings of this study, carried out in Bangalore city of Karnataka state of India, depict the same story of every city of India. The pace at which LULC change has occurred in Bangalore in the past 20 years has caused huge impacts on the city’s natural environment. Image classification results show a sudden growth of urban areas (built-up) and a decrease in critical land covers such as vegetation, water, and land. The primary water resources of Bangalore, i.e., water canals and the Kaveri River, are decreasing over time. The harmful effect of overpopulation and the resultant urbanization has reduced the quality and quantity of primary living amenities such as water, clean air, and living space [37,38]. Traffic congestion in Bangalore is among the other negative impacts of rapid urbanization, contributing to the increase in UHI events. In various other cities of India, similar trends in urbanization and decreasing critical LULC have been observed, such as Delhi, Jaipur, Kolkatta, Chennai, Mumbai, Srinagar, and others [39–41]. Urbanization has flourished at the cost of dwindling water bodies, forest cover, and soil infertility. While we have looked at the impact of urbanization on natural LULC, there is still much more work to conduct on the relationship between economic growth and changes in natural ecosystem services.

Furthermore, land surface temperature (LST) plays a significant role in analyzing the land surface energy budget [42]. LST provides valuable information for developing land surface states and land–atmosphere exchange [43]. By evaluating and observing LST changes, the government can take an essential parameter for diagnosing temperature problems. More UHI event assessments are to be conducted to acquire greater information about Bangalore’s surface temperature. Based on the comparison of three UHI temperature events, we observed that such events over the years in the same month have increased in intensity (3.25 °C from 2001 to 2021). Many such events would be taking place, thus affecting the urban climate system. In addition to altering the regional climate, higher urban temperatures also significantly influence human health and the economy [44]. Higher temperatures necessitate more and more indoor cooling systems such as air conditioners, coolers, and fans. These ultimately cost more energy, and finally, it also acts as a positive feedback loop to the climate system [45].

Overall, unsustainable urbanization could halt the growth of India in the coming decades if appropriate steps are not taken into consideration. It is to be noted that a significant proportion of the world’s poor is estimated to live in India [46]. According to World Bank estimates for 2005, in India, 41.6 percent of the total indigenous population have below USD 1.25 per day income [47]. According to 2010 data, an estimated 37.2 percent of Indians lived below the poverty line, according to the World Development Report [39]. The latest UNICEF evidence demonstrates that 1 in 3 impoverished people globally are reported in India, with 42% of the country under five [48,49]. The 2011 Global Hunger Index (GHI) report ranks India among the three countries. The GHI increased from 22.9 in 1996 to 23.7 in 2011, with 78 of 81 developing countries being studied, such as Pakistan, Bangladesh, Nepal, Kenya, Nigeria, and Uganda [50]. Since its first five-year plan, the Indian government has initiated several programs such as support for food, other needs and enhanced access to loans, improved farming technology, price subsidies, and education [51]. In the latest World Bank report, India has well pursued its poverty reduction targets [52]. With all these developmental indices, if the present trend of urbanization continues in India, densely populated urban centers will rise. Therefore, an efficient strategy to implement all these schemes is necessary; otherwise, from the current trends in urbanization and the
current environmental degradation in India, the success rate of all the SDG goals shall not be so efficient.

SDG-11 is the solution for India and can only be achieved by a multi-tier approach that includes past assessments, socio-economic parameters governing the proliferation of urban centers, and how the whole process influences the earth system \([53,54]\). The government of India needs to rethink its attitude towards catering to the needs of the current urban centers to create such urban centers that are sustainable in the first place, and then allow populations to migrate towards them in a phased manner. There are examples of such centers in India, such as Ahmedabad and New Delhi \([55–63]\). This study thus directly tried to report the ongoing urbanization scenarios in one of the cities of India and the necessity for planning, monitoring, and managing various local-, regional-, and national-level programs for efficient urban policies to mitigate climate change and UHI effects.

However, it must be noted that the results presented in this work related to LST change are event-based, and the actual observation might not be so worrisome. As discussed in the methodology, we used the 8-day average LST data for the month of April from 2001 to 2021, which was the highest in that year (UHI event). The monthly average is far lesser in intensity. Since we aimed to assess the role of urban growth in increasing the LST of the region, it was therefore prudent to use such an event-based statistical parameter. Moreover, such events are, in fact, the UHI events that take place in every city but are often neglected in scientific assessment due to averaging of the time step required in the analysis (e.g., monthly, seasonal, or yearly). On the other hand, required time step LST averages do not depict such intensity and variability, and our work has tried to represent it. To further assess the role of urban growth on the LST change in the cities of India and other south-Asian countries, the probability distribution of high-intensity UHI events needs to be assessed against higher temporal frequency LULC change estimations.

5. Conclusions

We provided a methodology to assess the impact of the fast growth of urban centers on the increase in the intensity of UHI events, which is very important in the purview of the goals of SDG-11 of the United Nations. This paper presents the result of the LULC change detection of the Bangalore district of Karnataka over 20 years and its relationship with the increased temperature of the UHI events. It was observed that the decreasing trend of natural resources, such as water, vegetation, and land, coincided with the increasing urbanization between 2001 and 2021. Data analysis clearly shows that LULC changes were significant from 2001 to 2021. The support vector classifier tools used for the supervised classification in the present study proved to be among the best classifiers for analyzing urban growth. Analysis of LULC transformation is a very dominant factor in understanding the potential threats to agricultural practices, ecological communities, and accurate planning for urban development. Unplanned expansion of built-up is a significant problem associated with cities such as Bangalore. In 20 years, we found that built-up increased by 87.62%. Vegetation and water bodies decreased by 40% and 30%, respectively. Furthermore, based on the census of the 2001 and 2011 censuses, Bangalore’s population increased from 5.7 million to 8.7 million. In 2021, the population will reach around 12 million. We further found land surface temperature, on average, increased by about 0.34 °C per year in urban settlement areas of Bangalore during the UHI events of April 2001 and 2021, in contrast to 0.14 °C per year in non-urban areas. The non-linear mixed effects model results showed contrasting trends in the LST increase at urban and non-urban locations, which provided certainty that urbanization affects the temperatures in the study area. In order to manage the rising temperature in the urban centers, emigration to these centers has to be managed sustainably. Modern lifestyles, technological advancements, and other facilities attract people from rural to urban areas but must be checked and planned sustainably if cities are saved from such a man-made disaster.

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