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Harnessing Machine Learning Algorithms to Model the Association between Land Use/Land Cover Change and Heatwave Dynamics for Enhanced Environmental Management

Kumar Ashwini ¹ , Briti Sundar Sil ², Abdulla Al Kafy ^{3,*} , Hamad Ahmed Altuwaijri ⁴ , Hrithik Nath ^{5,6}  and Zullyadini A. Rahaman ⁷

¹ Department of Civil Engineering Chaibasa Engineering College, Jhinkpani 833215, Jharkhand, India; kumar_rs@civil.nits.ac.in

² Department of Civil Engineering, National Institute of Technology, Silchar 788010, Assam, India; bssil@civil.nits.ac.in

³ Department of Geography & the Environment, The University of Texas at Austin, 305 E 23rd St, Austin, TX 78712, USA

⁴ Department of Geography, College of Humanities and Social Sciences, King Saud University, Riyadh 11451, Saudi Arabia; haaltuwaijri@ksu.edu.sa

⁵ Department of Civil Engineering, Khulna University of Engineering & Technology (KUET), Khulna 9203, Bangladesh; hrithik@uctc.edu.bd

⁶ Department of Civil Engineering, University of Creative Technology Chittagong (UCTC), Chattogram 4212, Bangladesh

⁷ Department of Geography & Environment, Faculty of Human Sciences, Sultan Idris Education University, Tanjung Malim 35900, Malaysia; zully@fsk.upsi.edu.my

* Correspondence: abdullaalkafy@utexas.edu or abdulla-al.kafy@localpathways.org



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Abstract: As we navigate the fast-paced era of urban expansion, the integration of machine learning (ML) and remote sensing (RS) has become a cornerstone in environmental management. This research, focusing on Silchar City, a non-attainment city under the National Clean Air Program (NCAP), leverages these advanced technologies to understand the urban microclimate and its implications on the health, resilience, and sustainability of the built environment. The rise in land surface temperature (LST) and changes in land use and land cover (LULC) have been identified as key contributors to thermal dynamics, particularly focusing on the development of urban heat islands (UHIs). The Urban Thermal Field Variance Index (UTFVI) can assess the influence of UHIs, which is considered a parameter for ecological quality assessment. This research examines the interlinkages among urban expansion, LST, and thermal dynamics in Silchar City due to a substantial rise in air temperature, poor air quality, and particulate matter PM_{2.5}. Using Landsat satellite imagery, LULC maps were derived for 2000, 2010, and 2020 by applying a supervised classification approach. LST was calculated by converting thermal band spectral radiance into brightness temperature. We utilized Cellular Automata (CA) and Artificial Neural Networks (ANNs) to project potential scenarios up to the year 2040. Over the two-decade period from 2000 to 2020, we observed a 21% expansion in built-up areas, primarily at the expense of vegetation and agricultural lands. This land transformation contributed to increased LST, with over 10% of the area exceeding 25 °C in 2020 compared with just 1% in 2000. The CA model predicts built-up areas will grow by an additional 26% by 2040, causing LST to rise by 4 °C. The UTFVI analysis reveals declining thermal comfort, with the worst affected zone projected to expand by 7 km². The increase in PM_{2.5} and aerosol optical depth over the past two decades further indicates deteriorating air quality. This study underscores the potential of ML and RS in environmental management, providing valuable insights into urban expansion, thermal dynamics, and air quality that can guide policy formulation for sustainable urban planning.

Keywords: machine learning; urban microclimate; heatwave; thermal comfort; artificial neural network; environmental management

1. Introduction

Rapid urbanization has the potential to advance economic and social development. However, it is also to blame for several environmental and human health issues [1]. The average temperature of the land's surface has seen a rise of 0.6 °C from 0.2 °C since 1861, and it is expected to rise by another 2 °C to 4 °C in the next 100 years [2]. One of the most crucial environmental parameters is surface temperature, affecting the earth's ecosystem and daily human activity [3]. Numerous urban planning and development projects impact the economy, the social environment, and the change in land cover [4]. In India, most cities are unplanned and crowded within a small administrative region, even though there are many planned cities throughout the world. Like other developing nations, India has seen a tremendous increase in its population [5]. An unfavorable population increase is detrimental to sustainable development and changes in land cover. The land use and land cover (LULC) configuration in each city differs according to city characteristics, scheduling, and periods. Cities like Delhi, Lucknow, Patna, etc., have undergone rapid population expansion, which enhances the expansion of unplanned urban areas and increases construction work and unorganized road networks [6,7]. Researchers have found decreased vegetation, loss of biodiversity, and increased urban areas in the northeastern part of India [7–9]. Monitoring a reasonable composition of LULC plays a vital role in sustainable growth and contributes to repairing the damaged living environment. Evaluating changes in LULC is crucial for the effective execution of water resource management plans and strategies [10]. The modifications in LULC have become larger and more complicated as a result, caused by human activity and ecological changes such as the expansion of farming the ground, the partition of forests, industrialization, and urbanization [11]. The shift in LULC distribution in a given region resulted from a consolidation of natural and human components [12]. Increasing the amount of urbanized land is not going to assist in helping people live better in cities. A crucial method for assessing the efficacy of urban development programs is to track shifts in LULC [11]. Because of the rapid economic development and increasing population, the challenge for resilient urban functionality is even more sophisticated [13,14].

The main causes of profound LULC changes are urbanization, industry, and specialized construction. On the other hand, they drive rapid urban growth and the expansion of the economy or competitiveness of cities [15]. In contrast, they show negative impacts such as an increase in air pollution, which vanguards the degradation of biodiversity, and land degradation and provokes the urban heat island (UHI) effect [16–18]. UHIs refer to metropolitan regions that endure greater temperatures than the surrounding areas [19]. The perusal of data discloses escalated UHI consequences on climate change. The resolution of UHIs under the circumstances is a desideratum with prior constraints of the added greenhouse gas (GHG) effect and global warming [20]. Many studies suggest that ongoing urban development designs without mediation further degrade urban climates, thereby intensifying urban temperatures [21]. Natural terrains including vegetation and water bodies absorb and re-emit less heat than man-made structures, which absorb and re-emit more heat [22,23]. This will further accelerate climate change, increase air pollution, and reduce natural resources, hindering urban biodiversity and speeding up the UHI impact. Various studies have confirmed that the UHI effect is attributed to heat flux distinctions among urban and rural areas. It is directly proportional to the population; a decrease in the amount of green space, a slower wind speed as a result of inadequate urban ventilation, and the accumulation of solar radiation as a result of the extensive use of construction materials lead to an increase in UHI intensity [18,24,25]. Nowadays, land surface temperature (LST) is receiving more attention as a measure of urban and sustainable development because an increase in LST leads to the development of UHIs [26]. LST is linked to modified LULC, temperature fluctuation, climate change, and global warming [25]. The LST is affected by any significant change in the vegetating zone or modification of water bodies into an impermeable layer. Urban areas are more imperceptible as higher LST in city areas are registered, thus helping to develop UHIs and reducing the environmental sustainability of

cities [25]. The use of land that generates urban sprawl linked to planned cities cannot be promoted in traditional cities. An effective LULC strategic plan to limit unplanned urban development and to increase green coverage requires lightening the detriments of UHI in the contemporary era in pursuit of the Sustainable Development Goals. Because of its harmful effect on public health, UHI effects are recognized as a phenomenon. In urban areas, the temperature is usually 3.5 °C to 4.5 °C more than in remote regions [27]. In the year 2018, there were 182 heat-related deaths reported, out of which 119 deaths were caused by heat and 63 were related to urban heat, which increased by 8.2% in 2020 [28,29]. Cities gradually consolidate orderly development through intervention from city planners and the government. However, the problems left, such as urban traffic congestion, the disorder in urban development, and UHIs, must be emphasized. The UHI effect is usually the most adverse impact of LULC change in numerous cities [30].

The Urban Thermal Field Variance Index (UTFVI) is used extensively to define the UHI effect [31]. Because of anthropogenic activities, the density of the UTFVI is higher in urban regions, and it is also higher than in the adjacent remote areas [4]. The UTFVI causes adverse effects on local wind patterns, which increase mortality rates, reduce comfort and raise death rates, affect air quality and moisture, and cause indirect economic loss [32]. The excess heat emitted by the UTFVI causes a stronger upward motion, which leads to more rain showers and thunderstorms. The UHI effect is also responsible for creating contaminants such as ozone that lead to water and air quality dilution [33]. As per reports during the COVID-19 lockdown, temperature reduction, air and surface water quality, and the UTFVI effect were improved in urban areas as there were minimum transportation and construction activities during that period [34–37]. Forecasting future UTFVI impacts can be useful for identifying potential heatwave zones and assisting municipal officials in developing policies for minimizing the UHI effect and achieving a healthy environment in the future. A number of variables, including heatwaves, changes in the surfaces of the earth, and illumination intensity, influence LST's capacity to cause UHI and UTFVI occurrences. A crucial element in the UHI impact is the shift in LULC. The most important variable impacting LST is the change in the proportion of LULC types. Predicting future LULC change and assessing LST linkages can aid in limiting the spread of the UHI and UTFVI phenomena. By anticipating future events, LULC estimations can help to stop socio-economic development-based environment projection [38]. Many researchers have undertaken numerous simulation studies to categorize LULC's link to LST, assisting newly developing cities with sustainable development strategies in the future [38–41]. Several explicit spatial models, such as Artificial Neural Network (ANN) and Cellular Automata (CA) models with the integration of RS and GIS (remote sensing and Geographical Information System) technology, successfully produce the forecast results [7,42–44]. While forecasting future LULC and LST scenarios is common, predicting yearly UTFVI impacted by LULC variation is a novel idea from the RS perspective.

This analysis is distinctive since it attempts to forecast UTFVI variations within the administrative boundary of Silchar City. It has been noted that Silchar City is experiencing issues such as temperature rise and decreased air quality because of an increase in PM_{2.5}. For this reason, this city was included in the National Clean Air Program (NCAP), whose goal is to monitor and address comprehensively the issues caused by rising pollution across the nation. Expanding urban areas in a disorganized manner, population growth, and improper drainage systems lead to flash floods in the rainy season [45,46]. As the city is positioned on the banks of the Barak River, which is one of the important rivers in the northeastern part of India, its course has been affected by the change in land cover around the river [47]. The sinuosity index has been increased, and the river's course is shifting, leading to land loss [48]. The alluvial part of the Barak River basin lies in the Cachar district, which is more urbanized and faces problems like groundwater depletion, riverbank erosion, flash floods, and increasing temperatures in comparison with other parts of the Barak River basin in the last two or three decades [47,49,50].

While previous studies have examined LULC changes and their impacts on urban environments, there are several limitations in the existing literature. Most studies focus on larger metropolitan areas, overlooking the unique challenges faced by smaller, rapidly growing cities like Silchar. Additionally, there is a lack of comprehensive analysis that integrates LULC changes, LST variations, and UTFVI predictions over extended periods. Our study addresses these gaps by providing a detailed analysis of LULC changes, LST variations, and UTFVI predictions for Silchar City from 2000 to 2040. We utilize advanced machine learning techniques, specifically CA and ANN models, to predict future scenarios with high accuracy. Furthermore, we offer insights into the environmental challenges faced by tier-2 cities in developing countries, which are often understudied. By integrating multiple environmental indicators, including LULC, LST, UTFVI, AOD, and PM_{2.5}, we provide a holistic understanding of urban environmental changes. This research presents a novel approach to understanding and predicting the impact of urbanization on land cover and the thermal environment in Silchar City. It offers new insights into how rapid urbanization alters these crucial environmental parameters and introduces the concept of projecting annual UTFVI impacts influenced by LULC variations, a first in the field of remote sensing. This study's intellectual merit lies in its comprehensive examination of the heat island effect and its potential implications. By assessing the linkages between LULC change and LST, valuable knowledge can be gained to mitigate UHI effects. This research utilizes advanced spatial models, including ANN and CA, demonstrating the innovative use of remote sensing and GIS technologies. The impact of this study is extensive, providing urban planning tactics and guiding sustainable improvement in growing cities. This is particularly important for Silchar City, which faces rising temperatures, decreased air quality, and increased PM_{2.5} levels, necessitating its inclusion in the NCAP. Understanding environmental shifts and their implications due to urbanization will support formulating government policies. Moreover, the findings are anticipated to significantly contribute to achieving a healthier environment in the future, in line with the Sustainable Development Goals. This research has potential implications not just for Silchar City but also for other regions experiencing similar urbanization-induced environmental changes. It is an essential step towards enhancing our comprehension of urban ecosystems and advocating sustainable city development. The innovations applied in this study allow for a more comprehensive assessment of urban environmental changes and their potential impacts, providing valuable insights for urban planners and policymakers in similar rapidly growing cities.

2. Materials and Methods

2.1. Study Area

Our research is centered around Silchar City, a key node within the Barak River basin. Situated along the banks of the Barak River (Figure 1), Silchar holds a significant position within the basin. The city's predominantly flat landscape makes it an ideal location for human settlement. The Barak River has its source in the Japvo mountain ranges in Manipur, starting at an altitude of 3015 m. The river courses southwards along the slope, extending to Tipaimukh, a point of intersection for three states including Assam, Manipur, and Mizoram. At this juncture, the river sharply changes its course, forming a hairpin bend before entering the Cachar district. The river then flows westward through Assam's Barak Valley, eventually crossing the border into Bangladesh. Upon entering Bangladesh, the Barak River splits into the Surma and Kushiara rivers [50].

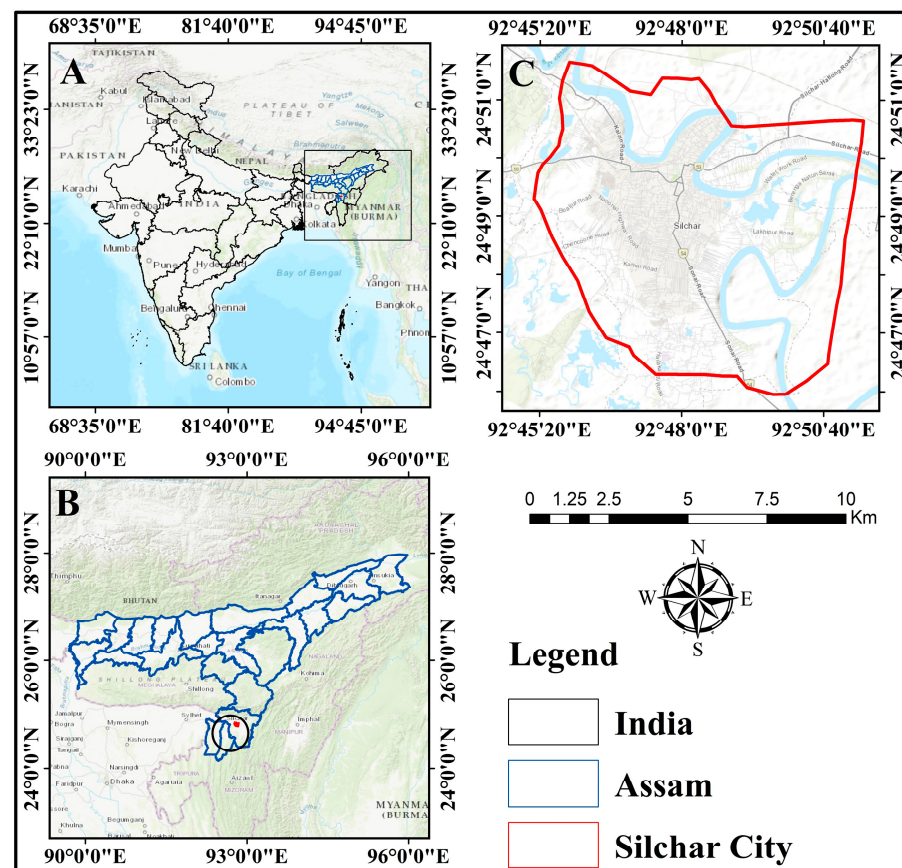


Figure 1. Location map of the study area (A) India and Assam, (B) Assam and Silchar, and (C) Silchar City.

Silchar serves as the administrative hub for the Cachar district in Assam, situated in the northeastern region of India. The city's geographical coordinates extend from $24^{\circ}47'$ N to $24^{\circ}52'$ N in latitude and $92^{\circ}45'$ E to $92^{\circ}52'$ E in longitude. This region has a subtropical climate that is warm and humid. It receives 2500–4000 mm of annual rainfall, with more than 80% of that falling between April and October, and the mean annual T_{max} and T_{min} temperatures range between 17.74°C and 19.67°C and 25.47°C and 29.25°C , respectively. The vegetation at the river's edges is sparse. Bamboo brakes (Banbusoidae), wet and dry grassland (Phragmmittiskaraka), and scrublands are the most popular plant habitats [51]. Prolific tea farms line the region's borders. The city has a total of 228,985 people [52,53]. From 2000 to 2020, the annual population increase was reported to be 29.24% (Figure 2). The progression from Figure 2 panels A to C clearly illustrates an increase in population density, especially in the city center, quantifying and spatially representing the rapid urbanization process in Silchar over the study period. Silchar's limited economic growth has been attributed to its geographical isolation and insufficient infrastructure and communication networks. However, in recent years, the town has seen a surge in business activity and has been steadily growing [53]. The town generates approximately 100 tons of municipal garbage daily, which is also responsible for the increase in cancer patients [53,54]. The former prime minister of India, Smt. Indira Gandhi named this place an "Island of Peace". Silchar serves as a gateway to the neighboring states of Manipur and Mizoram.

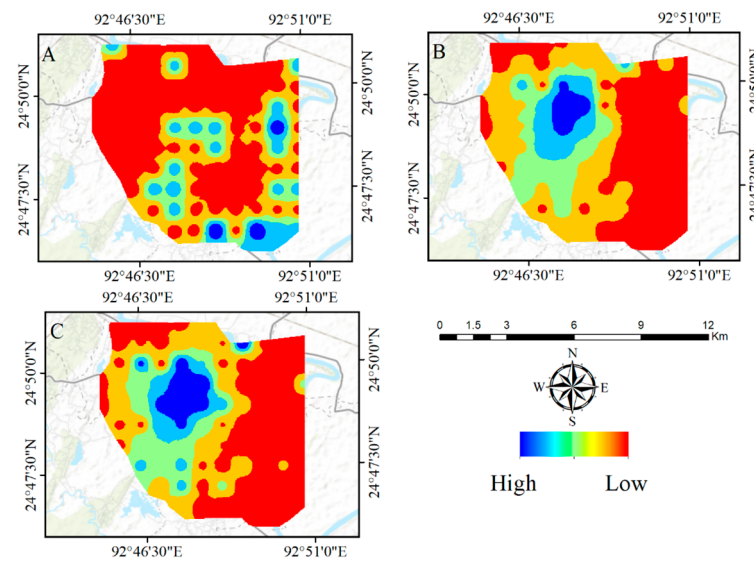


Figure 2. Population density in (A) 2000, (B) 2010, and (C) 2020.

2.2. Methods

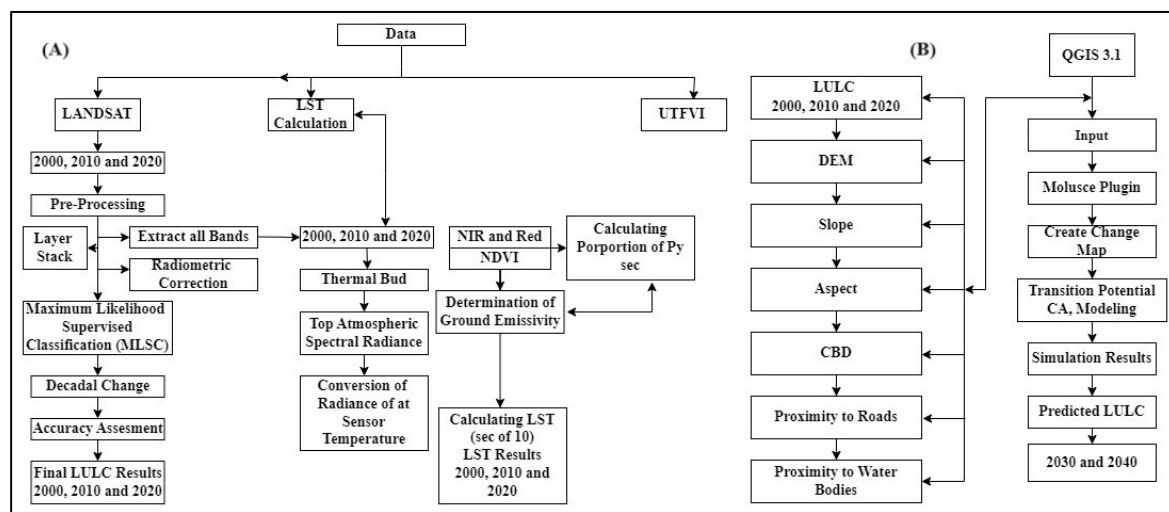
This study employed multi-spectral Landsat 8 OLI and Landsat 4–5 TM satellite images from 2000, 2010, and 2020, which are publicly accessible through the United States Geological Survey (USGS). These images were downloaded from Earth Explorer. We selected images from the summer and winter seasons to mitigate seasonal variability within one-month intervals. Because of some imaging errors, only images from November were considered for the analysis (Table 1). These Landsat satellite images, already geometrically and radiometrically corrected, required no further image-to-image geo-rectification or registration. The maximum cloud cover threshold was set to less than 5% to obtain images with minimal cloud interference. Additionally, other data were used to predict future land use and validate the AOD and PM_{2.5} data trends from the past two decades concerning the city's changing land use (Table 2). Figure 3 presents a methodological flowchart of this study. It outlines the key steps from data collection to LULC classification, LST calculation, and UTFVI analysis, to the final prediction of future scenarios. This flowchart provides a clear overview of this study's methodological approach, helping readers understand the logical progression of this research.

Table 1. Landsat data description.

Year	Data	Acquisition Date	Sensor	Temporal Resolution	Spatial Resolution	Source
2000	Landsat 5	11 November 2000	TM	16 days	30 m	USGS
2010	Landsat 5	23 November 2010	TM	16 days	30 m	Earth Explorer
2020	Landsat 8	18 November 2020	OLI	16 days	30 m	https://earthexplorer.usgs.gov/ (accessed on 1 November 2021)

Table 2. Additional data used in this study.

Data	Year	Resolution	Source
Digital elevation model, Cartosat I-V3		30 m	BHUVAN https://bhuvan.nrsc.gov.in (accessed on 1 November 2021)
Landscan (Population Density)	2000, 2010, and 2020	1 km	ORNL https://landscan.ornl.gov/ (accessed on 1 November 2021)
Aerosol optical depth (MODIS AOD)	2000–2020	1 km	https://lpdaac.usgs.gov/ (accessed on 1 November 2021)
Particulate matter (PM _{2.5})	2000–2020	1 km	CAS (IIT Delhi)
MODIS LST (MOD11A1v006)	2000–2020	1 km	https://lpdaac.usgs.gov/ (accessed on 1 November 2021)

**Figure 3.** Methodological Flowchart (A) LST and UTFVI estimation (B) LULC prediction approach.

2.2.1. LULC Classification of Landsat Images

We generated a True Color Composite (TCC) using an appropriate combination of bands. We classified the satellite images into five categories as follows: water bodies, vegetation, agricultural lands, built-up areas, and others (Table 3). This categorization was performed for 2000, 2010, and 2020 using the Maximum Likelihood Supervised Classification (MLSC) technique in ArcGIS Version-10.6.1 software. Over 150 training samples were taken for each class to create the LULC maps, and their accuracy was validated with ground truths from available Google Earth image data. We calculated the overall accuracy of the LULC for each year under study.

Table 3. Land cover description.

LULC Types	Description
Vegetation	Bushes, stunted trees, or forest
Agricultural land	Fallow land, grassland, cropland, park, and playground
Water bodies	Ponds, wetlands, lakes, reservoirs, and rivers
Built-up	Road, industrial building, residential, and commercial
Others	Landfill sites, open space, bare soils, sand, and vacant land

2.2.2. Calculation of LST

Landsat imagery with thermal bands was used to determine LST for 2000, 2010, and 2020. The sensor on the Landsat collects thermal data and records it as Digital Numbers (DNs). We employed a seven-step procedure for Landsat 8 OLI images (2020) and a three-step procedure for Landsat 4–5 TM images (2000 and 2010) to calculate LST. The initial step involved converting the thermal band DN value into spectral radiance.

Step 01: Thermal band DNs were converted to radiance by using Equations (1)–(3) [55], where V = DN of the thermal band.

$$R_{TM} = \frac{V}{255}(R_{max} - R_{min}) + R_{min} \quad (1)$$

$$R_{max} = 1.896 \left(\text{mW} \times \text{cm}^{-2} \times \text{sr}^{-1} \right) \quad (2)$$

$$R_{min} = 0.153 \left(\text{mW} \times \text{cm}^{-2} \times \text{sr}^{-1} \right) \quad (3)$$

Step 02: The R_{TM} was converted to LST in Kelvin using Equation (4), where K_1 = (Constant) = 1260.56 K, $K_2 = 607.66 \text{ (mW} \times \text{cm}^{-2} \times \text{s}^{-1})$, and b (spectral range) = 1.239 (μm).

$$LST_K = \frac{K_1}{\ln \left(\frac{K_2 \times b}{R_{TM}} + 1 \right)} \quad (4)$$

Step 03: After obtaining LST in Kelvin, Kelvin was converted to degrees Celsius by using Equation (5).

$$LST_{0C} = T_K - 273 \quad (5)$$

2.2.3. Calculation of LST for Landsat 8 OLI

Step 01: Bands 10 and 11, which are the thermal infrared sensor (TIRS) and bands 2–5, which is the OLI sensor, were used individually to convert the raw satellite image to spectral radiance (SR) using Equation (6) [56,57], where L = atmospheric SR in $\text{watts} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1}$, L_{max} = maximum SR of respective bands, L_{min} = minimum SR of the respective bands, and $DN_{max} = Q_{cal \ max} - Q_{cal \ min}$ = difference between the minimum and maximum sensor's calibration.

$$L = \left(\frac{L_{max} - L_{min}}{DN_{max}} \right) \times \text{Band} + L_{min} \quad (6)$$

Step 02: The data of the TIRS band were then converted from SR to BT with the help of thermal constants given in the metadata file using Equation (7) [58], where K_2 and K_1 are band-specific constants and BT is the brightness temperature (Celsius).

$$BT = \left(\frac{K_2}{\ln \left(\frac{K_1}{L_{\lambda}} + 1 \right)} \right) - 273.15 \quad (7)$$

Step 03: Then, NDVI was calculated, which is an essential parameter in the calculation of LST for Landsat-8, with the help of band 5 and band 4 using Equation (8) [59,60], where the range of NDVI is -1 to $+1$.

$$NDVI = \frac{NIR(B5) - R(B4)}{NIR(B5) + R(B4)} \quad (8)$$

Step 04: With the help of the highest and lowest value of NDVI, P_v (Proportion of Vegetation) was calculated using Equation (9) [59–61]:

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \quad (9)$$

Step 05: Then, LSE (Land Surface Emissivity) was calculated with the help of P_v , as calculated above, using Equation (10) [62].

$$LSE = 0.004 \times P_v + 0.986 \quad (10)$$

Step 06: Equations (11) and (12) were then used to calculate LST in degrees Celsius [59,62], where σ = the Boltzmann constant (1.38×10^{-23}) JK^{-1} , h = Planck's constant (6.626×10^{-34} J-s), and c = the velocity of light (2.998×10^8 ms^{-1}).

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

$$\rho = h \frac{c}{\sigma} = 1.438 \times 10^{-2} \text{mk} \quad (12)$$

Step 07: The final LST was calculated using Equation (11) with the help of the average of bands 10 and 11. For this, cell statistics in ArcGIS Version-10.6.1 licensed software was used.

2.2.4. UTFVI Calculation

Comparing several images from the same year to assess the thermal characteristics of a region can be misleading because of atmospheric variations throughout the year. Hence, we used a normalized method (Equation (13)) to present the UHI scenarios within the same year [39]. We further calculated the UTFVI using Equation (14) [63,64], and based on these values, categorized the city's thermal comfort into six ecological evaluation indices [65].

$$\text{UHI} = \left(\frac{(T_s - T_m)}{\text{SD}} \right) \quad (13)$$

where T_s is LST, T_m is LST mean, and SD is the standard deviation. We further used LST images and mean LST to calculate the UTFVI using Equation (14) [63,64].

$$\text{UTFVI} = \left(\frac{(T_s - T_m)}{T_m} \right) \quad (14)$$

where T_m is the mean LST and T_s is the LST in degree Celsius ($^{\circ}\text{C}$). Subsequently, the value of the UTFVI was bifurcated into six ecological evaluation indices [65], which were used to evaluate the city's thermal comfort. The thermal variability index (UTFVI) of Silchar City was divided into six categories as follows: excellent, good, normal, bad, worse, and worst [37,66].

2.2.5. LULC Estimation

The CA model is frequently utilized worldwide to predict LULC because it incorporates dynamic and static features of LULC change with great precision [12,67,68]. This unique mathematical model operates on an infinite, regular lattice with a finite number of dimensions, composed of individual cells [69]. Each cell's attribute is defined by a specific set of transition rules [70]. In the context of this study, a CA model script was developed considering various factors that contribute to the growth of built-up areas. To simulate the 2030 and 2040 LULC, we used dependent variables including major road networks, waterbodies, the central business district (CBD), in this case, Silchar City, a digital elevation model (DEM), slope, and aspect, which play a vital role in built-up growth. Additional steps were taken to create a buffer zone for the road network, water bodies, and the central business district at intervals of 1, 1, and 3 km, respectively. The vector layers were rasterized at a pixel size of 30 m, and a constant extent was extracted to align with the projection, geometry, and cell size of the previous layers. Cartosat-1, V3 DEM data, which are freely available from the Indian Earth Satellite data site BHUVAN [71], were utilized to prepare the slope and aspect maps at a 30 m spatial resolution. MOLUSCE provides an easy-to-use interface with its user-friendly modules and functions. It is an open-source QGIS Plugin that takes the previous year's LULC (in this case, 2000, 2010, and 2020) and supporting factors as input and gives projected LULC. The LULC maps of 2000, 2010, and 2020 were used to predict LULC for the years 2030 and 2040 (Figure 4). An area change analysis between the

years 2000 and 2000, 2010 and 2020, and simulated 2030 was performed. For 2040, we used simulated 2020 and 2030 and produced transition matrices for these respective years.

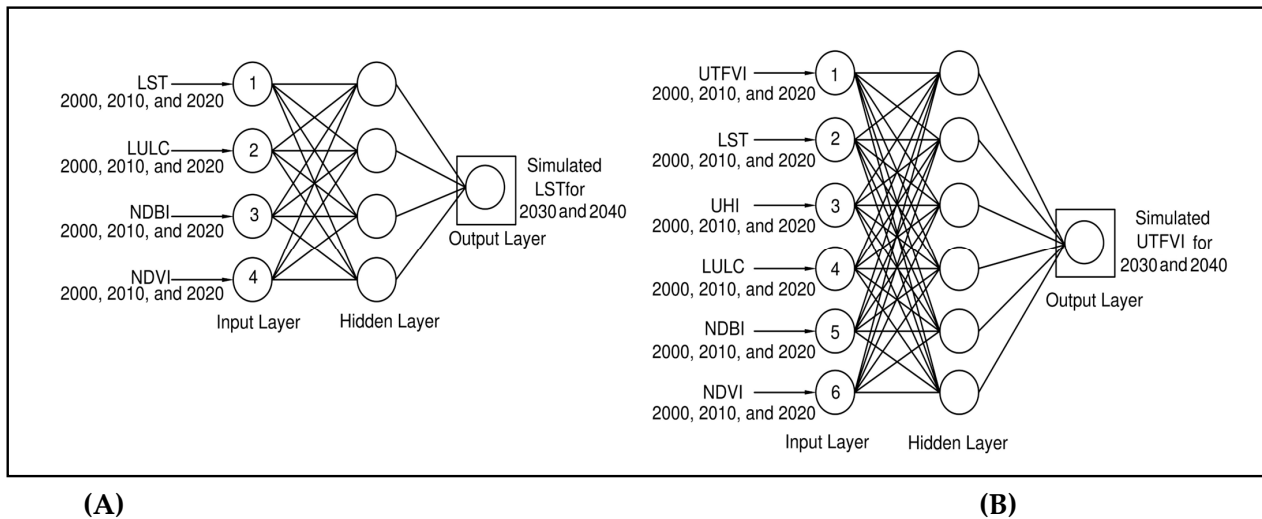


Figure 4. ANN model architecture for predicting (A) LST and (B) UTFVI.

2.2.6. ANN Modeling

To run the ANN model, the LST and UTFVI influencing factors such as NDBI, NDVI, and LULC were first extracted for respective years for the Silchar City region. We further matched these images' projections, pixel sizes, and geometries using QGIS software 3.1 and extracted each point value of the variables. To simulate LST for 2030 and 2040, we used the previous year's LULC, LST, NDVI, and NDBI images, which were in an interval of 10 and 20 years. These variables were supplied into the MATLAB ANN model as input parameters.

TRAINLM, as the training function, LEARN_GDM, as the adaption learning function, PURELIN, as the transfer function with two layers and a total of 10 neurons, were used. Then, the network was trained using algorithms like Random Data Division and Levenberg–Marquardt for training. It uses a total number of 8 iterations with a gradient of 2.27×10^{-8} . In the simulation part, the sample data for the year the simulation was to be performed were selected and the network. To simulate LST 2030, the input data (NDBI, NDVI, LST, and LULC) from 2000 or 2010 and target data for LST 2020 were used. As evident in Figure 5, the points were closer to the linear line, which indicated that the model was perfectly constructed with minimal error. The observations were further supported by the R and RSME regression statistics computed using Equations (19) and (20) for the measured and predicted values of LST and the UTFVI for the year 2020, wherein the standard error was on the order of 0.41 in the predicted value. We then used the sample data (NDBI, NDVI, LST, LULC) and Equation (15), which gave a simulated LST of 2030. To simulate LST 2040, input data (NDBI, NDVI, LST, and LULC) and Equation (16) were used. To predict UTFVI for the years 2030 and 2030, input variables (UTFVI, LST, LULC, UHI, NDVI, and NDBI) and Equations (17) and (18) were used [38]. Once the LST prediction was made, the same model was used to predict the UTFVI for the years 2030 and 2040. The network diagram for the prediction of LST and the UTFVI for the years 2030 and 2040 is shown in Figure 5. The close alignment of points along the diagonal line indicates high prediction accuracy. This figure validates the effectiveness of our ANN models in predicting these crucial environmental parameters.

$$\text{LST}(t + 10) = f[\text{LST}(t), \text{LST}(t - 10), \text{LULC}(t), \text{LULC}(t - 10), \text{NDBI}(t), \text{NDBI}(t - 10), \text{NDVI}(t), \text{NDVI}(t - 10)] \quad (15)$$

$$\text{LST}(t + 20) = f[\text{LST}(t), \text{LST}(t - 20), \text{LULC}(t), \text{LULC}(t - 20), \text{NDBI}(t), \text{NDBI}(t - 20), \text{NDVI}(t), \text{NDVI}(t - 20)] \quad (16)$$

$$\text{UTFVI}(t + 10) = f[\text{UTFVI}(t), \text{UTFVI}(t - 10), \text{LST}(t), \text{LST}(t - 10), \text{UHI}(t), \text{UHI}(t - 10), \text{LULC}(t), \text{LULC}(t - 10), \text{NDBI}(t), \text{NDBI}(t - 10), \text{NDVI}(t), \text{NDVI}(t - 10)] \quad (17)$$

$$\text{UTFVI}(t + 20) = f[\text{UTFVI}(t), \text{UTFVI}(t - 20), \text{LST}(t), \text{LST}(t - 20), \text{UHI}(t), \text{UHI}(t - 20), \text{LULC}(t), \text{LULC}(t - 20), \text{NDBI}(t), \text{NDBI}(t - 20), \text{NDVI}(t), \text{NDVI}(t - 20)] \quad (18)$$

$$R = \frac{\sum (T_{\text{obs}} - \bar{T}_{\text{obs}})(T_{\text{model}} - \bar{T}_{\text{model}})}{\sqrt{\sum (T_{\text{obs}} - \bar{T}_{\text{obs}})^2 \sum (T_{\text{model}} - \bar{T}_{\text{model}})^2}} \quad (19)$$

$$\text{RSME} = \sqrt{\frac{\sum [T_{\text{obs}} - T_{\text{model}}]^2}{n}} \quad (20)$$

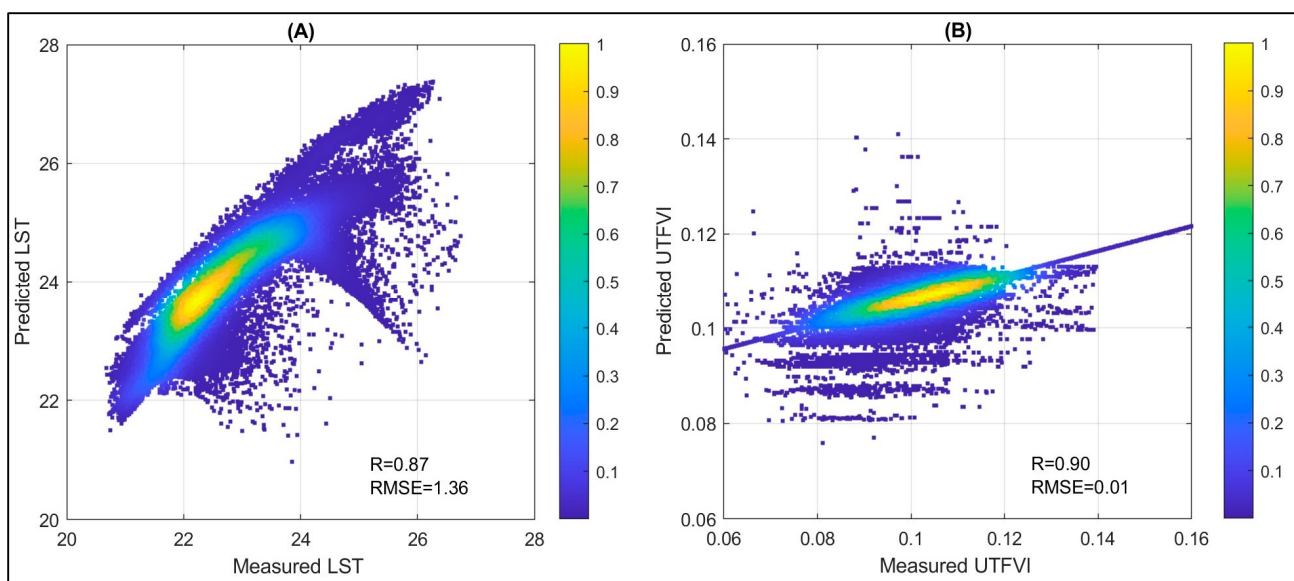


Figure 5. Predicted and measured (A) LST and (B) UTFVI for 2020.

3. Results

Satellite-based multi-year LULC, LST, UHI, and UTFVI maps were prepared and analyzed for the Barak River basin in Silchar City. It was found that LST, the UHI, and the UTFVI showed an increasing trend within the city area. To identify the future scenario of these changes within Silchar City, the prediction and spatiotemporal distribution analysis of the simulated LULC, LST, and UTFVI were also performed as discussed in Section 3, and trends in atmospheric data like MODIS AOD data and PM_{2.5} data were also used to justify the outcomes of this study.

3.1. LULC Change

With the help of the MLSC method, we classified the Landsat image (TM/OLI) into five classes and calculated the area change in LULC from 2000 to 2020 (Figure 6). The color-coded maps clearly show the spatial distribution of different land use categories and how they changed over time. It can be observed that the trend changed for various classes, like a gradual increase in water bodies and the built-up area with a decrease in agricultural land and vegetation areas during the study period. Figure 7 quantifies the decadal percentage change in area for each LULC category from 2000 to 2020. The bar graph clearly shows a significant increase in settlement areas and a corresponding decrease in agricultural land and vegetation. This visualization helps quantify the urbanization trends observed in the LULC maps.

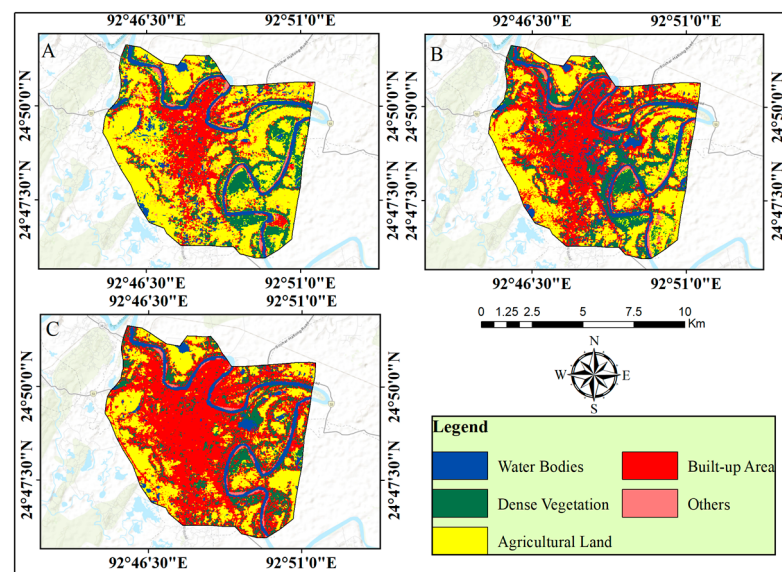


Figure 6. LULC for the years (A) 2000, (B) 2010, and (C) 2020.

Table 4 shows the LULC area statistics and their changes. We can observe that the urban land area increased from 18.34 km² (23.96%) to 34.52 km² (45.1%) from 2000 to 2020. In this same period, a significant decrease can also be noticed in vegetation and agricultural land from 13.6 km² (17.78%) and 34.59 km² (45.21%) to 11.13 km² (21.73%) and 21.45 km² (28.02%), respectively. Within 20 years, a positive net change and growth can be observed in the urban region of 16.17 km² (21.14%) with an adverse change in agricultural land of −13.15 km² (17.17%), as illustrated in Figure 7. The findings revealed that urban areas replace agricultural land, vegetation, and other classes. This replacement can be due to several factors such as rural-to-urban migration due to employment opportunities, better living standards, and massive urban development. Hence, unplanned urban sprawl causes stress on that particular area's natural resources and damages the vegetation cover, which impacts the health of the environment and its sustainability [72,73]. Migration from rural regions to urban regions not only increases the population of a city but also increases the energy demand [74]. The predicted rise in various sectors like industries, residential, transportation, power generation, and buildings would increase air pollution [75]. Particulate matter with a diameter of less than 2.5 µm and prolonged suspension times, referred to as PM_{2.5} [76], is one of the air pollutants that has multiple short-term and long-term adverse health impacts [77]. These particles are created from fuel combustion and atmospheric chemical processes [78–80]. To further support our findings on the environmental impacts of urbanization, we analyzed the trends in AOD and PM_{2.5} levels over the past two decades. Figure 8 shows that the city's AOD and PM_{2.5} experienced an increasing trend in the last two decades (2000 to 2020). The increasing trends in both parameters correlate with the urbanization patterns observed in the LULC analysis, providing additional evidence of the environmental impacts of rapid urban growth.

Table 4. LULC area statistics for 2000, 2010, and 2020.

LULC Class	Area in km ²			Net Change in %
	2000	2010	2020	
Water bodies	8.18	9.42	7.51	−0.87
Vegetation	13.64	12.96	11.13	−3.27
Agricultural land	34.59	25.22	21.45	−17.17
Settlements	18.34	27.52	34.52	21.14
Others	1.79	1.42	1.93	0.18

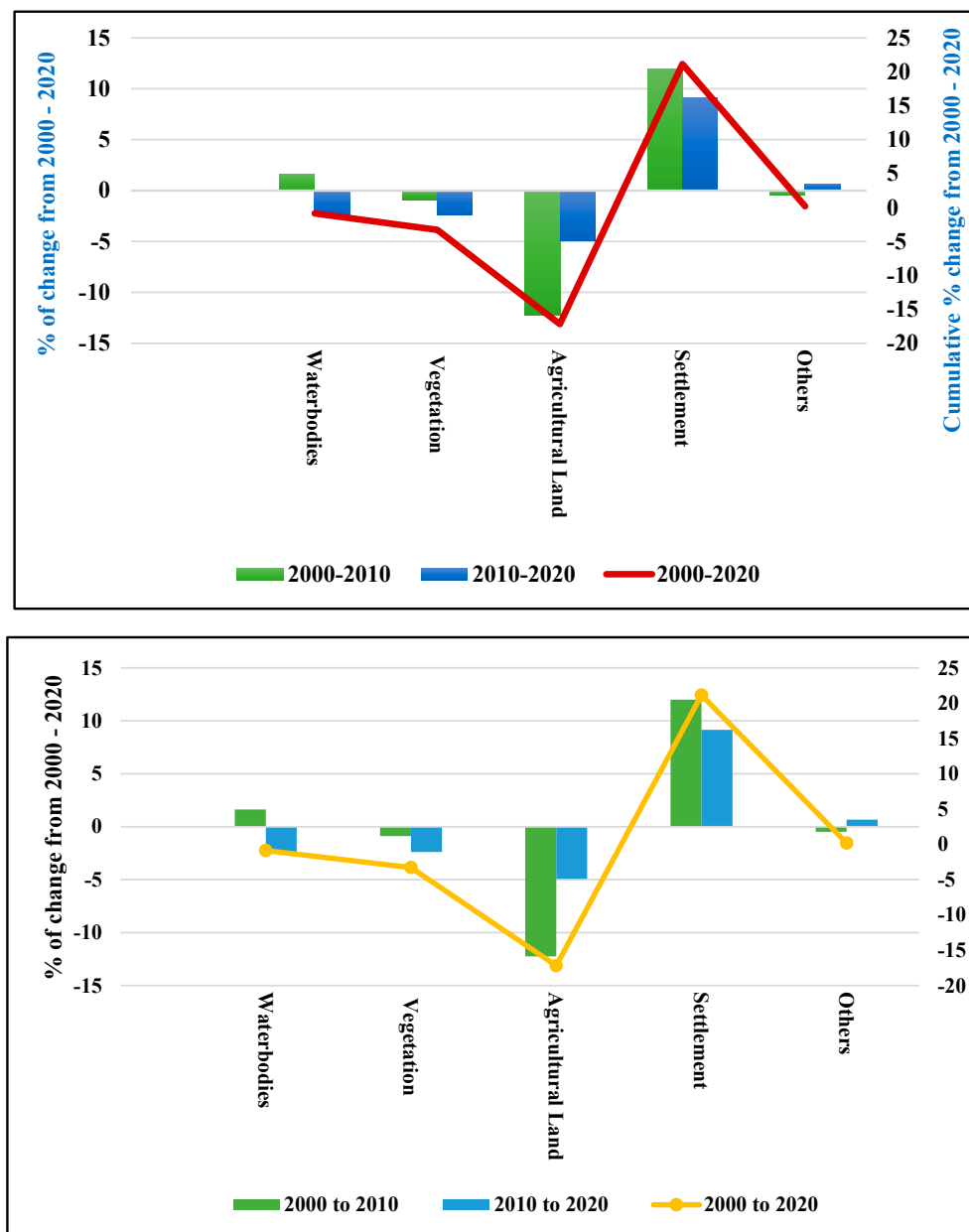


Figure 7. Decadal % change in area from 2000 to 2020.

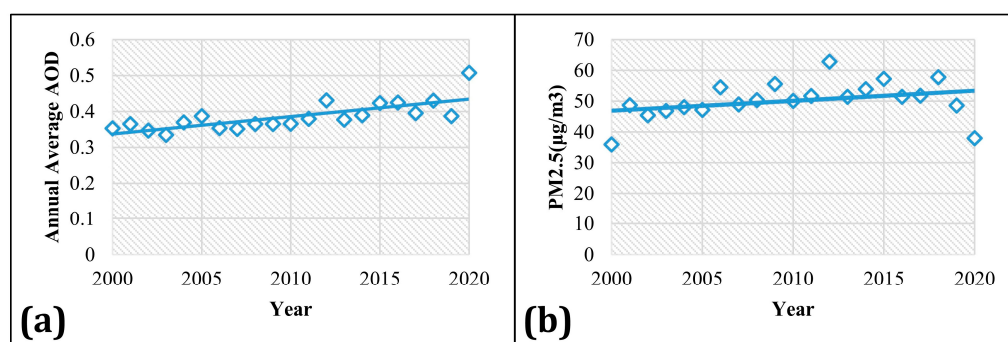


Figure 8. Annual average trend in (a) MODIS AOD and (b) PM_{2.5} for the last two decades in the study area.

3.2. Accuracy Assessment of LULC Classification

The evaluation of accuracy for the years 2000, 2010, and 2020 yielded results of 94%, 91.3%, and 92.6%, respectively, with a kappa coefficient that varied between 0.81 and 0.91 (Table 5). Other research endeavors, such as those conducted in Umabadda Natural Reserved Forest, South Kordofan, Sudan [81], Majuli river island [8], and the metropolitan areas of Dhaka, Rajshahi, and Cumilla in Bangladesh [17,38,82], reported comparable outcomes in their accuracy assessments, with kappa coefficients ranging from 0.8 to 0.9. A kappa coefficient exceeding 0.5 is deemed acceptable for forecasting LULC alterations [83,84]. A kappa coefficient surpassing 0.7 is viewed as exceptional, while coefficients between 0.6 and 0.79 are seen as substantial. A coefficient of 0.59 or lower suggests a poor or moderate consensus [85]. In this study, the overall accuracy and kappa coefficient fall within the exceptional range. The classified imagery for the years 2000, 2010, and 2020 demonstrated superior user and producer accuracy across nearly all categories in each year. Among all the classified images, water bodies and other land categories were classified with almost 98% accuracy, primarily because of their clear distinction from other classes. In the year 2000, the classification of water achieved the highest accuracy, with producer and user accuracies of 98.5% and 99.7%, respectively. Likewise, for agricultural land, the highest accuracy was achieved in 2000, with producer and user accuracies of 98.31% and 100%. As indicated in Table 5, the overall accuracy measures, including producer and user accuracy, suggest that this classification is reliable and can be used for further research.

Table 5. Accuracy assessment.

Year	User Accuracy					Producer Accuracy					Overall Accuracy
	Water Bodies	Vegetation	Agricultural Land	Settlements	Others	Water Bodies	Vegetation	Agricultural Land	Settlements	Others	
2000	98.5	98.9	98.3	94.9	96.1	99.7	99	100	96.11	99.3	95.14
2010	96.8	94	96.3	94.95	99	97.5	98.5	96.5	98.2	93.83	96.32
2020	98.3	95.86	93.2	95.68	100	96.2	96.9	93.21	95.8	91.74	98.51

3.3. Prediction of Future LULC

The preceding LULC maps for the years 2000, 2010, and 2020 were utilized to predict the LULC scenario for the years 2030 and 2040 (Figure 9). The predicted results show that the urban area will be 47.63% of the total area in 2030 and will increase by another 2.69%, covering 50.32% of the total area in 2040. It is evident from the figure that the built-up areas in 2040 increased significantly in every direction as compared with the year 2000. The east, east-south-east, and south-south-east directions will see the most noticeable increase in the urban area, while the west and north-west directions will see the least. This is because the terrain in the west and north-west is highly undulated and suitable for tea farming, whereas the terrain in the east and northeast is flat and suitable for settlement (Table 6).

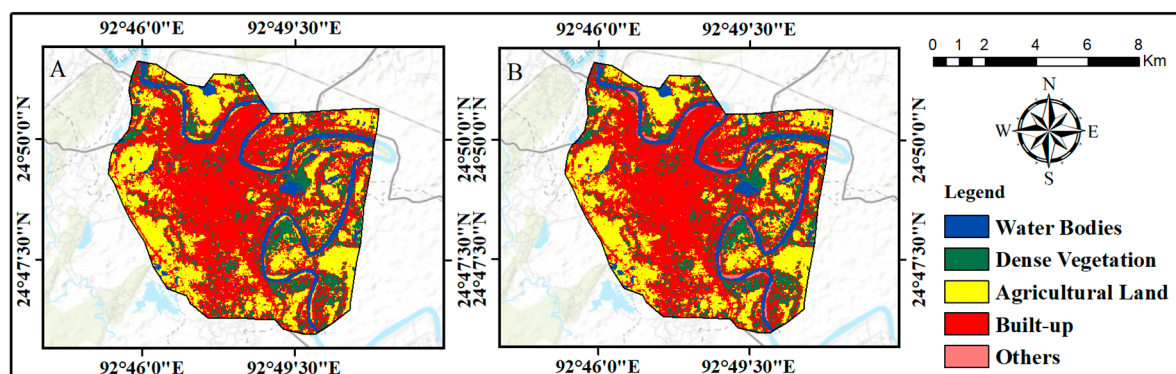


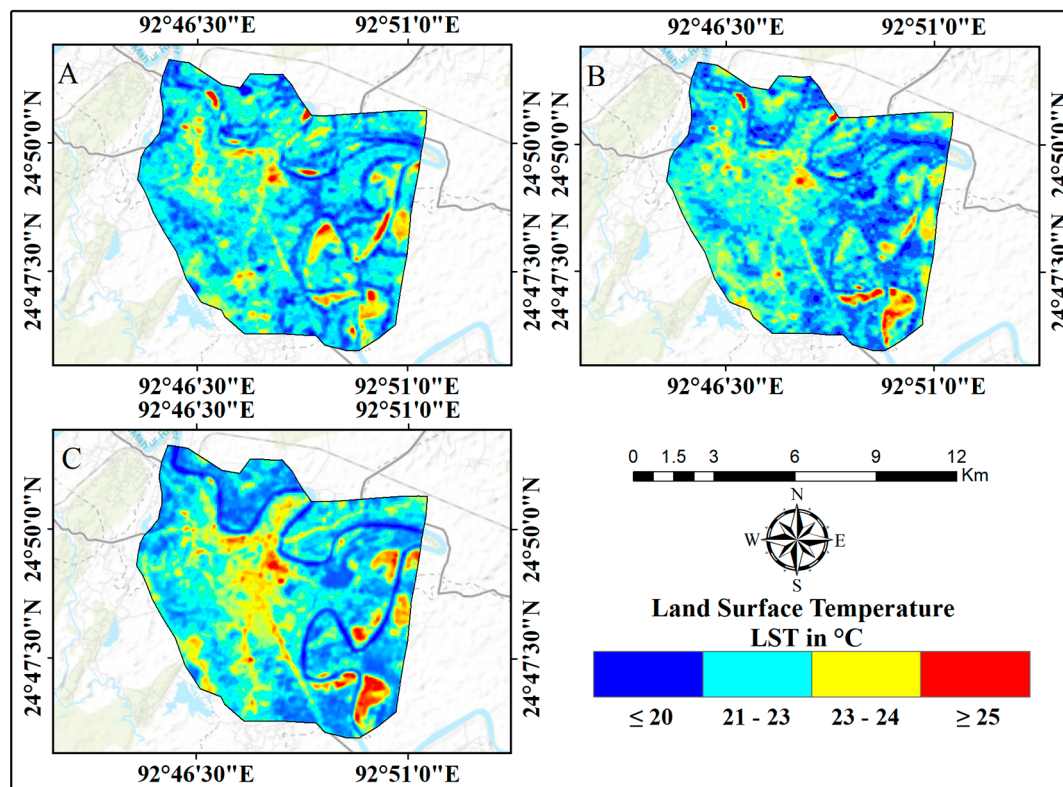
Figure 9. LULC for the years (A) 2030 and (B) 2040.

Table 6. LULC area statistics for the years (A) 2030 and (B) 2040.

LULC Class	2030		2040		% Change	Net % Change from 2000–2040
	Area in km ²	Area in %	Area in km ²	Area in %		
Waterbodies	9.2	12.02	6.6	8.62	−3.39	−2.06
Vegetation	10.59	13.83	11.1	14.5	0.66	−3.32
Agricultural land	19.14	25.01	19.42	25.37	0.36	−19.82
Settlements	36.45	47.63	38.51	50.32	2.69	26.35
Others	1.16	1.52	0.91	1.18	−0.32	−1.15

3.4. LST Variation

Figure 10 displays the LST distribution for (A) 2000, (B) 2010, and (C) 2020. The color gradient from blue to red represents increasing temperatures. The expansion of higher temperature areas (orange and red) over time, particularly in urban centers, visually demonstrates the UHI effect associated with urbanization. It can be seen that the temperature is higher near the city and the sandy region (which comes under other classes in LULC in (A) 2000, which expanded from (B) 2010 to (C) 2020. The area having LST greater than 25 °C is increased by 10% (Table 7).

**Figure 10.** LST for the years (A) 2000, (B) 2010, and (C) 2020.**Table 7.** LST distribution.

Year	2000		2010		2020	
	Area in km ²	Area in %	Area in km ²	Area in %	Area in km ²	Area in %
Temperature (°C)						
≤21	43.52	56.86	36.31	47.45	21.18	27.68
21 to 23	25.32	33.08	28.78	37.61	28.45	37.14
23 to 25	6.57	8.58	8.83	11.54	18.32	23.94
≥25	1.13	1.46	2.62	3.42	8.59	11.23

3.5. Prediction of LST

The predicted LST for the next two decades (2030 and 2040) of the Silchar City region, where population density is much higher, is shown in Figure 11. To predict the LST distribution over the city region, the ANN model was used, which gave a high prediction accuracy R and RSME (0.87 and 1.36, respectively), and the results are shown for the high-to-low temperature variation and next two-decade prediction for the city region only (Figure 5). The increased predicted LST can be due to rapid population expansion, urban development, and economic activities. Such an incrementing trend is important in achieving sustainable development [31,39]. Since they were based on historical LST data (2000–2020), the predicted findings show growing LST trends, with urban areas influencing the dominance of higher LST.

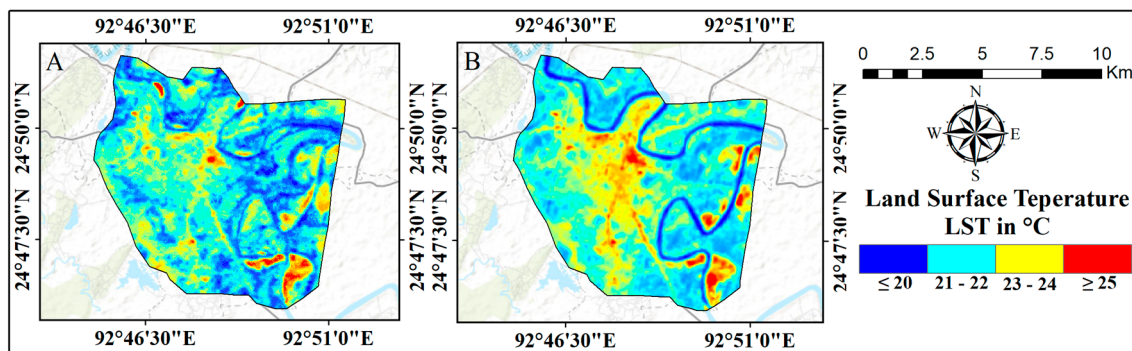


Figure 11. Predicted LST for (A) 2030 and (B) 2040.

Looking ahead, escalating urbanization activities coupled with a significant decrease in green spaces are expected to lead to a rise in LST and the subsequent impacts of UHI [86]. Factors such as the GHG effect, global warming, and alterations in surface properties also contribute to elevated LST, even in areas not experiencing rapid urbanization [87]. The projected LST illustrates an expected increase in temperature within the study area, which would intensify the effects of UHIs and the UTFVI. The exacerbation of the UHI effect can be attributed to factors such as increased energy consumption, escalating emissions of GHGs, and heightened air pollution. These factors pose potential risks to aquatic ecosystems and human health [88–90]. The increase in GHG concentrations is also a heat trapping factor and causes the UHI effect to increase [91], harms public health, lowers city wellness, and diminishes a city's ecological sustainability [92,93].

3.6. UTFVI Variation

As discussed above, the UTFVI provides information on ecology and urban health quality. Figure 12 shows the UTFVI variation over Silchar City from 2000 to 2020. It can be observed that over the city region, where the population density and development work are higher, the UTFVI value is also higher, and vice-versa, than the previous year's UTFVI (2000 to 2020). This shows an increasing trend, which indicates the future importance of UTFVI prediction and identifies the UHI's effect on the city region.

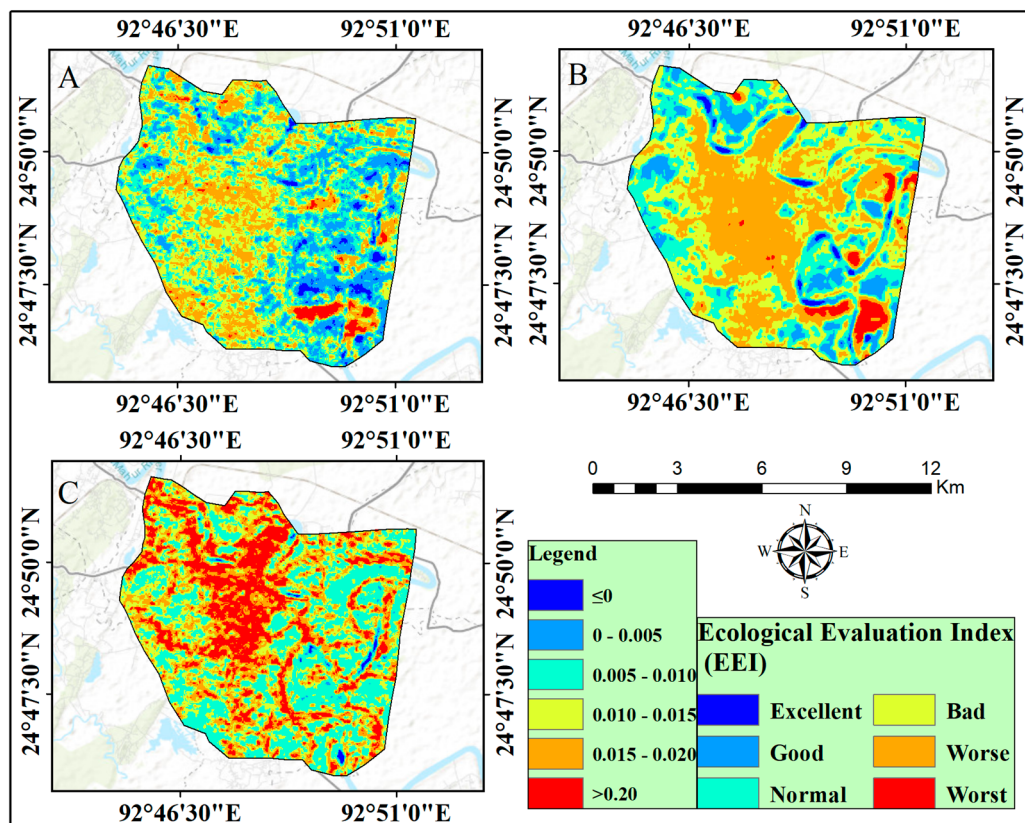


Figure 12. UTFVI for the years (A) 2000, (B) 2010, and (C) 2020.

3.7. Prediction of UTFVI

The ANN model was utilized to predict the UTFVI concentration over the city region, which gave a high prediction accuracy with R and RSME values of 0.9 and 0.01 (Figure 5). It is obvious from the predicted image that the UTFVI concentration over the city region is higher than the green space (Figure 13). The effects of vigorous to most vigorous UTFVI will be significantly increased with a minimization of the none-to-middle effects.

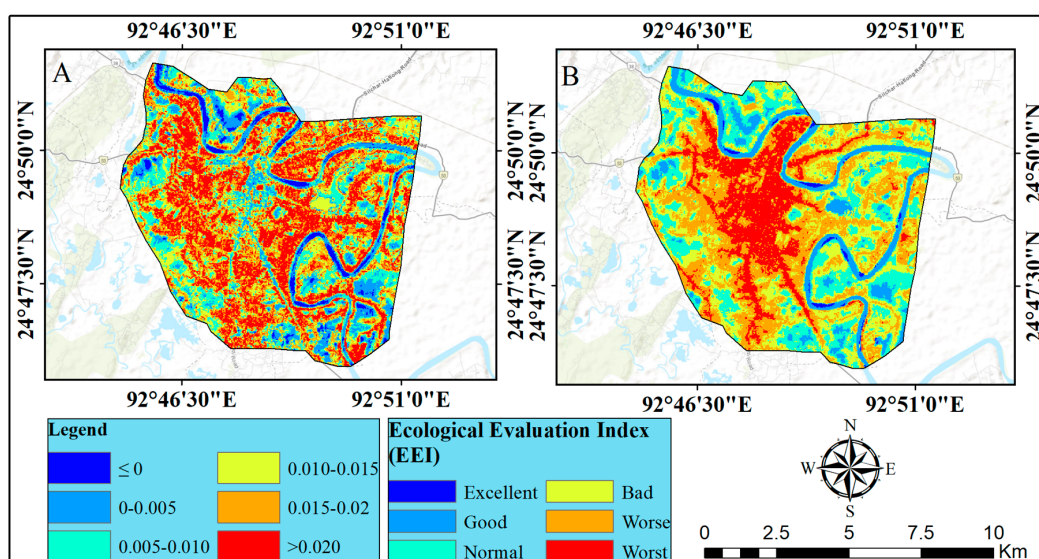


Figure 13. Predicted UTFVI for (A) 2030 and (B) 2040.

4. Discussion

4.1. LULC Change Analysis and Prediction

LULC change is a significant concern considering global dynamics, particularly concerning environmental and socioeconomic impacts [94,95]. These changes in LULC are known to affect various aspects of the environment directly and indirectly [96]. India has witnessed unprecedented urbanization since the 1991 economic reforms [97,98]. Much of this land transformation has occurred by converting farmlands into construction sites, contributing to the UHI effect in metropolitan areas like Wuhan, with increased impervious surfaces and decreased vegetation cover [99].

LULC research, natural resources management, environmental monitoring, and conservation initiatives extensively use remote sensing imagery to detect land use and cover changes [99,100]. The increase in population, particularly in India, the world's second-most populous country, is leading to the depletion of natural resources [101]. Global population predictions indicate an increase from 7.3 billion to 8.5 billion in 2030, 9.7 billion in 2050, and 11.2 billion by 2100 [102]. In 2023, India surpassed China and the USA to become the most populous country in the world [103]. The study area saw an estimated yearly population increase of 29.24% from 2000 to 2020 (Figure 2). According to the United Nations Department of Economic and Social Affairs (UNDESA), the global urban population was 34% in 1960 and 54% in 2014, and it is expected to reach 66% by 2020 [104], as illustrated in Figure 14. This graph contextualizes Silchar's urbanization within global trends, showing that the city's rapid urban growth aligns with broader global patterns of increasing urbanization.

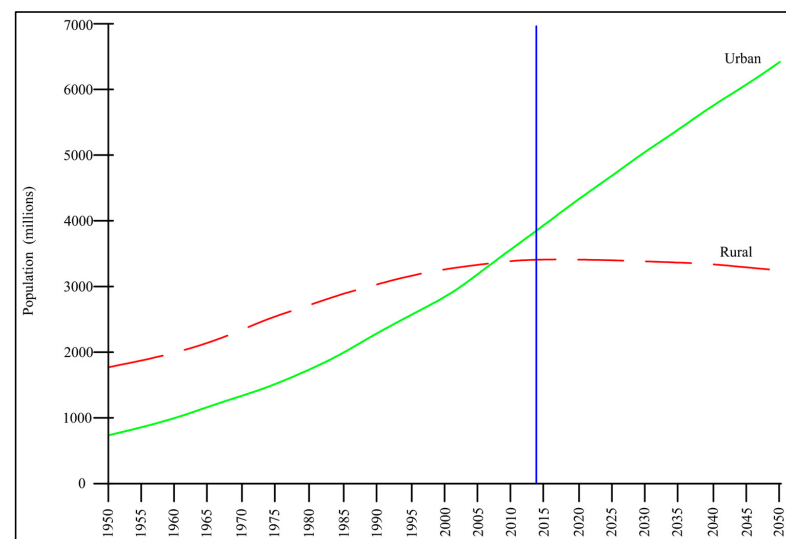


Figure 14. Urban and rural population of the world, 1950–2050 [104].

The Look East Policy is part of the Northeastern Region (LPE-NE) Vision 2020, implemented by the Prime Minister in July 2008. As per this policy, the main objectives were development in connectivity, infrastructure, trade, investment, and tourism in the northeastern part of India. Because of rapid construction and urbanization, the pollution level in Silchar City increased because it is kept as a tier-1 city under the NCAP, whose objective is to enhance the air quality of such polluted cities in India. In this study, the spatiotemporal patterns of LST and the UTFVI in relation to LULC changes in the City of Silchar were examined using Landsat data. The findings indicated that the chosen methodology can effectively track urban growth and monitor shifts in biophysical indicators such as LST, NDVI, and the UTFVI, as a consequence of LULC modifications. This version is original and should be safe to use in future manuscripts [105]. The introduction of new material and a variety of LULC adjustments and surface modifications have all contributed to the current situation in Silchar City. A LULC, LST, and UTFVI spatiotemporal analysis were used to investigate these impacts. It was shown that urbanization resulted in a shift in surface

conditions from cold to hot, which is similar to other researchers' findings [7,27,82,106]. The extent of these shifts implied that urbanization had a negative impact on environmental quality in the form of temperature variation in metropolitan regions. The Silchar LULC pattern evolved dramatically over the course of the investigation. The built-up area saw the most transformation, followed by agricultural land and bare terrain. The loss of agricultural land, vegetative cover, and bare ground to built-up expansion mostly drive peri-urban LULC changes. Compared with the base year 2000, the urban area will increase by 26.35% by the end of 2040 with a decrease of 19.82% in agricultural land and 3.32% in vegetative cover (Figure 15). This comprehensive view clearly shows the dramatic increase in built-up areas and the corresponding decrease in natural and agricultural land over the 40-year period. The expansion of the urban area is mostly in the east, east–southeast, and south–southeast directions (Figure 16). The directional map clearly shows the spatial pattern of urban growth, with areas indicating the primary directions of expansion. This visualization is crucial for understanding the spatial dynamics of urbanization in Silchar and can inform targeted urban planning strategies.

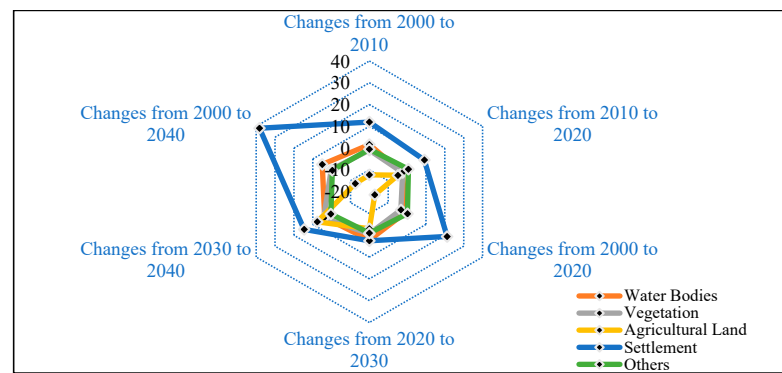


Figure 15. Overall percentage change in LULC from 2000 to 2040.

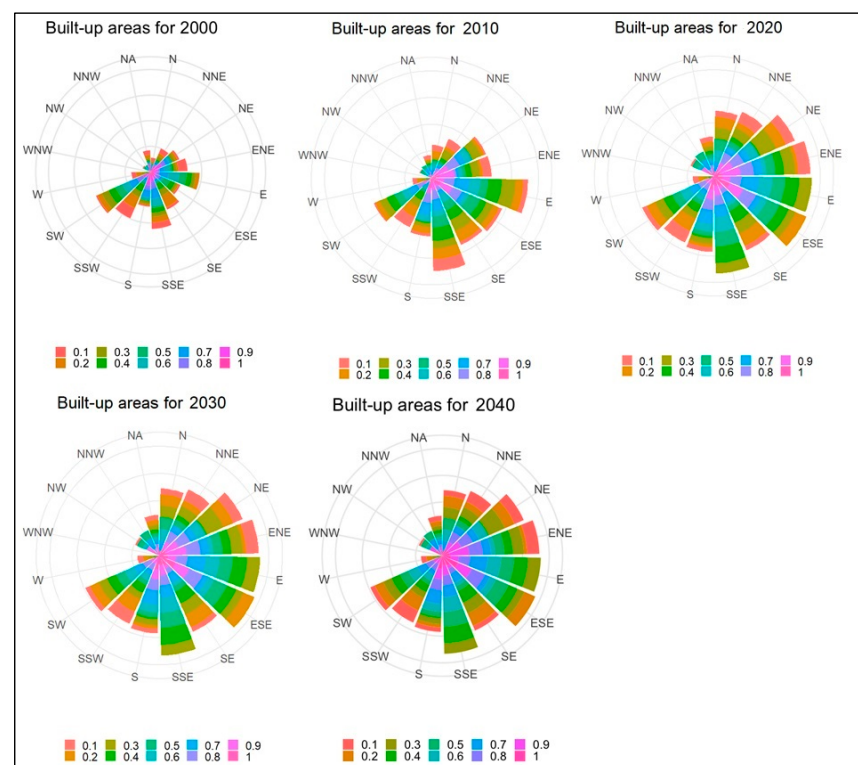


Figure 16. Directional change map of urban areas from 2000 to 2040.

4.2. Assessing and Predicting Surface Temperature Variability

LST is often a focal point for researchers as it is a critical parameter for investigating UHI effects within urban areas. A UHI, primarily attributed to urbanization and the use of heat-retaining materials in new land developments, is a result of LST analysis. LST forecasts can provide insights into future UHI patterns, impacts, and potential mitigation strategies over metropolitan regions. Accurately predicting LST could contribute significantly to energy savings, reducing air conditioning costs and associated CO₂ emissions, thus aiding in mitigating global warming [107]. LST increases, ranging from local to global scales, impact ecosystems significantly, making it an essential climate and biosphere element. LST represents the thermal radiation emission from land surfaces and the canopies of vegetated areas [108]. Particularly in Silchar's urban regions like Tarapur, Premtala, Meharpur Hospital Road area, Sonai Rangirkari Road, and Link Road area, a substantial increase in LST is projected—a rise of 4 °C by 2040 (Figure 12). Based on past LST data (2000–2020), the forecast indicates a rising LST trend influenced by urban areas. There is a predicted linear growth in regions with temperatures exceeding 25 °C, with a projected increase of 22% from the base year 2000 (Figure 17). The clear increase in high-temperature areas visually demonstrates the intensification of the UHI effect over the study period.

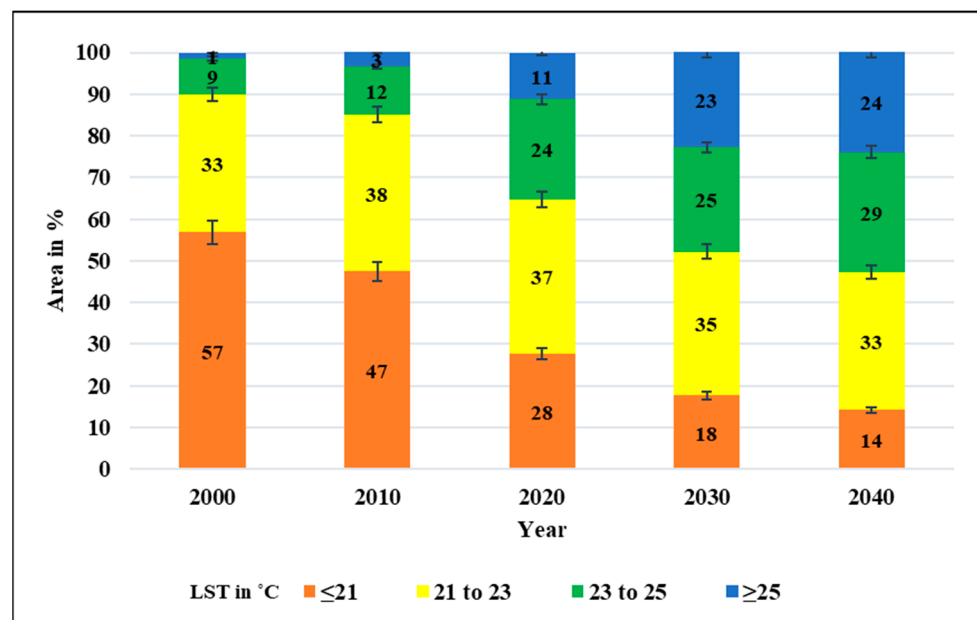


Figure 17. The overall change in the area statistics of LST from 2000 to 2040.

Rising urban development activities and a substantial decrease in green spaces will exacerbate LST and UHI effects in the future. Factors such as the GHG effect, global warming, and changes in surface features could increase LST in areas untouched by urbanization. The recorded increase in LST and the UTFVI suggests that the study area will face higher temperatures (Tables 7 and 8). The Intergovernmental Panel on Climate Change (IPCC) asserts that rising energy consumption, GHG emissions, and air pollution impact human and environmental health [2]. These increasing emissions adversely affect human health, urban wellness, and environmental sustainability. The practice of irrigating plantations and constructing water bodies using traditional human surface alteration methods created a “cool-green edge” and “cool-wet edge” in the old city and its outskirts. This led to a characteristic triangle distribution in this semi-arid area because of diverse surface climatic conditions. Multiple studies show an LST increase linked to urbanization [109], a trend observed in various Indian cities like Patna, Chandigarh, Lucknow, and Delhi [107,110–113]. Since LST and air temperature are proportional, an increase in air temperature would lead to an increase in LST. From 1860 to 2005, India's average surface temperature (ST) rose by 0.055 K/decade, mirroring global warming [114]. Consequently, the land surface temperature is expected to be

higher than the air temperature [115]. This temperature rise may adversely affect plant and animal species and human health [2]. The Representative Concentration Pathway (RCP) 4.5 data also indicate a positive Z value, signifying an increasing trend for Silchar City from 2000 to 2040 (Figure 18). The increasing trends in both $T_{\max}$ and $T_{\min}$ provide additional evidence of overall warming in the region, consistent with the LST and UTFVI trends observed in our study.

Table 8. Future LST distribution.

Year	2030		2040	
Temperature ($^{\circ}\text{C}$)	Area in km^2	Area in %	Area in km^2	Area in %
≤ 21	13.52	17.66	10.87	14.20
21 to 23	26.43	34.53	25.32	33.08
23 to 25	19.15	25.02	22.05	28.81
≥ 25	17.44	22.78	18.3	23.91

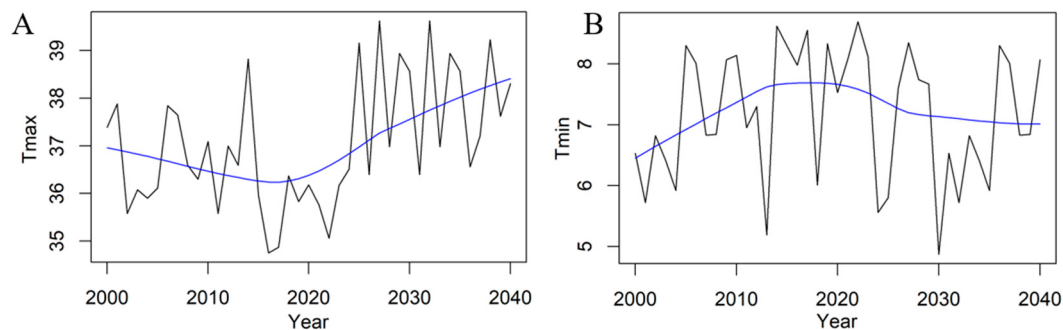


Figure 18. Trend in (A) $T_{\max}$ and (B) $T_{\min}$ for Silchar City using RCP4.5 data.

4.3. Assessing and Predicting the Variability in Urban Thermal Comfort

This study evaluated the ecological aspects of LST in Silchar City, primarily through UTFVI measurements. Notably, Silchar exhibits a range of EEI scores, with superior ones ($\text{UTFVI} < 0$) and inferior ones (0.02 or greater), as detailed in Table 9. The territory marked by the poorest EEI score is expected to expand by 7.16 km^2 by 2040, as presented in Tables 9 and 10. The UTFVI, as defined by Equation (14), is essentially the ratio of the mean LST in $^{\circ}\text{C}$ to the LST in $^{\circ}\text{C}$. Therefore, more significant data dispersion results in a larger UTFVI and, consequently, poorer EEI indices (Figure 12). Predominantly urban, high-density zones in the city center consistently display inferior EEI scores. By 2040, it is projected that areas with UTFVI values greater than 0.02 will increase by 18.98% (Figure 18).

Table 9. Area statistics of the UTFVI for the years 2000, 2010, and 2020.

Year	Excellent (≤ 0)	Good (0–0.005)	Normal (0.005–0.010)	Bad (0.010–0.015)	Worse (0.015–0.020)	Worst (>0.020)
2000	6.35	12.18	21.69	20.83	14.07	1.42
2010	4.79	10.23	17.72	21.61	20.05	2.14
2020	3.58	7.52	14.84	20.82	20.99	8.79

Table 10. Area statistics of the UTFVI for the years 2030 and 2040.

Year	Excellent (≤ 0)	Good (0–0.005)	Normal (0.005–0.010)	Bad (0.010–0.015)	Worse (0.015–0.020)	Worst (>0.020)
2030	3.25	6.32	16.08	19.95	17.99	12.95
2040	2.65	6.25	13.21	20.38	18.1	15.95

The UHI effect significantly influences the UTFVI, serving as a valuable indicator of environmental shifts due to human activities [82,116]. Factors such as uncontrolled and rapid urban growth and loss of green cover have intensified UHI effects in the studied area. Similar UTFVI trends have been detected in various cities globally [37,86,116–118].

During the COVID-19 lockdown, an impressive improvement in UTFVI values was observed, attributed to a 1–2 °C reduction in LST because of decreased human and transportation activities [37,119–122]. Built structures such as parking lots, skyscrapers, and sidewalks, indispensable to urban life, contribute to UHI effects, posing potential risks to human health, the environment, and the long-term sustainability of urban areas [90,123–125].

A variety of approaches can alleviate the impacts of UHIs and the UTFVI. These include the adoption of white roofing systems, the application of light-toned concrete materials, the establishment of green roofs adorned with plant cover, the widespread planting of trees, and the enforcement of environmentally friendly regulations. These regulations encompass standards for low-carbon fuels, the promotion of renewable energy sources, and the introduction of regulations for cleaner vehicles. These approaches are original and should be safe to use in future manuscripts [24,109,126–128].

The findings of this study have significant implications for green investment strategies in Silchar City and other rapidly urbanizing areas. The projected increase in built-up areas and the corresponding decrease in vegetation cover underscore the urgent need for targeted green investments. These could include urban forestry initiatives, such as tree planting programs in areas identified as future UHIs, to help mitigate temperature increases and improve air quality. Developing green infrastructure, like green roofs, permeable pavements, and urban wetlands, can manage stormwater, reduce the UHI effect, and enhance biodiversity. Investing in sustainable transportation, including public transit, bicycle infrastructure, and pedestrian-friendly spaces, can reduce vehicular emissions and improve urban air quality. Promoting and incentivizing energy-efficient buildings can significantly reduce energy consumption and associated greenhouse gas emissions. Additionally, investing in renewable energy sources, such as solar and wind, can help meet the growing energy demands of the city sustainably. By highlighting areas of rapid urban growth and environmental stress, our study provides a roadmap for prioritizing these green investments. This targeted approach can maximize environmental and social returns on investment, contributing to more sustainable and resilient urban development in Silchar City and beyond.

In light of the above interpretations, the following conclusions can be drawn from the study:

1. Changes in LULC often lead to increased infrastructure and decreased vegetation, which have detrimental impacts on ecosystems. Decreased vegetation results in reduced CO₂ absorption and increased surface impermeability, raising LST and, ultimately, leading to increased UHI.
2. Numerous studies predict substantial LULC changes due to urbanization in the next few decades. This will likely increase LST as more development and reflective surfaces are created.
3. In Silchar City, a tier-1 city under the Government of India's Clean Air National Program, aerosol optical depth and PM_{2.5} levels have risen over the past two decades.
4. Land cover transformation in Indian cities bears significant implications for land management and urban planning. Rapid conversion of agricultural land into residential and industrial land presents a major challenge. Therefore, sustainable development, guided by meticulous planning and environmental considerations, is crucial in this context.

5. Limitation of the Study

Despite the substantial insights generated from this study, certain inherent limitations arise from the nature of the data sources and methodologies employed. The entire analysis is grounded on freely accessible Landsat data provided by the U.S. Geological Survey,

which means the findings and interpretations are bound to the satellite's specific dates of image capture. A primary limitation is the use of only November images for analysis. This choice was necessitated by data quality issues, as images from other months were often obscured by cloud cover. During the downloading of Landsat data, a 5% cloud cover threshold was fixed, which further restricted the availability of clear images for the rest of the months. While November offers certain advantages for Silchar's context (post-monsoon clarity, moderate temperatures, and stable vegetation), it does not capture the full range of seasonal variations. This limitation potentially affects our understanding of seasonal dynamics in LULC, LST, and UTFVI. Future research could develop a more nuanced and comprehensive understanding by incorporating multi-seasonal image data into the analysis, particularly focusing on summer and winter months to capture the full range of annual variations. Utilizing advanced cloud-removal techniques or employing multi-sensor approaches could help overcome cloud cover issues in monsoon months, and integrating ground-based measurements with remote sensing data could help validate and refine satellite-based observations. An additional point of potential enhancement lies in the inclusion of directional maps, which could provide a more visually intuitive representation of the findings. Despite these research and estimation process constraints, the derived outcomes maintain a solid scientific grounding. The findings provide valuable insights for various stakeholders, including environmental engineers, policymakers, and city planners, informing their strategies to enhance urban management practices in cities. However, future studies should endeavor to overcome these limitations, aiming for a more comprehensive and seasonally informed analysis supplemented with more detailed and diverse data sources to bolster the accuracy and applicability of the research outcomes. This could include the use of higher resolution satellite data, the integration of socio-economic data, and the application of more advanced machine learning techniques for prediction and analysis.

6. Conclusions

The presented research provides a detailed examination of the future trends in LULC and LST changes within Silchar City in the Barak River basin. Landsat images were employed to shed light on the current status of the city and its potential future evolution. The findings indicate a probable 26% increase in residential areas by 2040, assuming urban development follows the pattern observed between 2000 and 2020. This anticipated growth correlates with a predicted 3% decrease in green spaces, 19% in farmland, and 2% in bodies of water. The most pronounced expansion of constructed areas occurred towards the east, east-south-east, and south-south-east, with minimal growth in the west and north-west from 2000 to 2020, a trend likely to persist until 2040. The research also reveals the presence of higher temperatures in barren soil areas compared with lower LSTs in vegetation and water bodies. The temperature increases over the past two decades average 0.95°C , indicating a potential deficit change pattern of 1.52. The process of swift urbanization emerges as a significant contributor to shifts in the urban climate and ecological balance. Notably, the North Meherpur subdivision of Cachar has experienced significant urban development, and the population density has grown in central Silchar near Premtala point. An estimated 21.14% of the land transitioned to constructed areas during the 2000 to 2020 timeframe, significantly impacting the rise in LST. The correlation between LULC and LST changes is evident, with increases in LST observed in urban areas under increased population pressure. The swift reduction in vegetation in urban locales plays a crucial role in environmental degradation. A large proportion of rural land has transitioned to census-designated town status because of the appeal of urban amenities and connectivity. The eastward trend in urban expansion suggests the potential future decline in rural agriculture. The CA model forecasts considerable decreases in green cover by 2030 and 2040, while the ANN model projects the future distribution of LST and the UTFVI, predicting over 30% of the variance. A data review from 2000 to 2020 at ten-year intervals indicates that augmenting urban green cover could significantly mitigate UTFVI and LST effects in

constructed regions. These findings could greatly assist urban authorities in fostering a sustainable, environmentally friendly cityscape by informing the strategic modification and replacement of LULC distributions. An optimal LULC distribution could help mitigate UHI effects, promote sustainable urban growth, protect ecosystem services, and improve daily living conditions.

This study demonstrates several key strengths, including its comprehensive approach to integrating multiple environmental indicators, the use of advanced machine learning techniques for future predictions, and its focus on a rapidly growing tier-2 city, which is often overlooked in urban environmental research. However, we also acknowledge certain limitations, such as the use of satellite imagery from only one month of the year and the inherent uncertainties in long-term predictions. Future research could address these limitations by incorporating multi-seasonal satellite imagery to capture seasonal variations in LULC, LST, and the UTFVI, integrating ground-based measurements with remote sensing data for more accurate environmental assessments, exploring the impacts of different urban development scenarios on environmental outcomes, investigating the socio-economic factors driving LULC changes and their environmental impacts, and developing more localized climate models to improve the accuracy of long-term environmental predictions. These future directions would further enhance our understanding of urban environmental dynamics and support more effective sustainable urban planning strategies.

Stakeholders such as policymakers, environmental engineers, and city planners stand to benefit significantly from this research. It advocates for implementing growth management policies to reduce urban heat problems related to LST. City planners and administrators are also encouraged to approach landscape planning from ecological and biodiversity viewpoints to mitigate the impact of LULC changes on LST in Silchar City. Further research could focus on exploring more detailed, localized strategies to counter the environmental challenges identified in this study. These strategies may include specific urban planning policies, land use guidelines, or environmental protection measures, which could enhance the livability and sustainability of Silchar City and similar urban environments.

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Abbreviations

TM: Thematic Mapper; OLI: Operational Land Imager; IPCC: Intergovernmental Panel on Climate Change; LULC: land use and land cover; LST: land surface temperature; UHI: urban heat island; UTFVI: Urban Thermal Field Variance Index; EEI: Ecological Evaluation Index; MODIS: Moderate Resolution Imaging Spectroradiometer; AOD: aerosol optical depth; ANN: Artificial Neural Network; CA: Cellular Automata; NCAP: National Clean Air Program; QGIS: Quantum GIS; RS: remote sensing; GIS: Geographical Information

System; ULBs: Urban Local Bodies; CPCB: Central Pollution Control Board; CBD: Central Business Development; MLSC: Maximum Likelihood Supervised Classification; NCAP: National Clean Air Program.

References

1. Nguyen, H.H.; Recknagel, F.; Meyer, W. Effects of Projected Urbanization and Climate Change on Flow and Nutrient Loads of a Mediterranean Catchment in South Australia. *Ecohydrol. Hydrobiol.* **2019**, *19*, 279–288. [\[CrossRef\]](#)
2. IPCC. *Climate Change 2001. Synthesis Report*; IPCC Fourth Assessment Report (TAR); Cambridge University Press: Cambridge, UK; New York, NY, USA; Port Melbourne, VIC, Australia; Madrid, Spain; Cape Town, South Africa, 2007.
3. Hunt, J.C.R.; Aktas, Y.D.; Mahalov, A.; Moustauoui, M.; Salamanca, F.; Georgescu, M. Climate Change and Growing Megacities: Hazards and Vulnerability. *Eng. Sustain.* **2017**, *171*, 314–326. [\[CrossRef\]](#)
4. Wang, H.; Zhang, Y.; Tsou, J.Y.; Li, Y. Surface Urban Heat Island Analysis of Shanghai (China) Based on the Change of Land Use and Land Cover. *Sustainability* **2017**, *9*, 1538. [\[CrossRef\]](#)
5. Van Schendel, W. *A History of Bangladesh*; Cambridge University Press: Cambridge, UK; New York, NY, USA; Port Melbourne, VIC, Australia; Madrid, Spain; Cape Town, South Africa, 2020.
6. Mishra, V.N.; Rai, P.K. A Remote Sensing Aided Multi-Layer Perceptron-Markov Chain Analysis for Land Use and Land Cover Change Prediction in Patna District (Bihar), India. *Arab. J. Geosci.* **2016**, *9*, 249. [\[CrossRef\]](#)
7. Ashwini, K.; Sil, B.S. Impacts of Land Use and Land Cover Changes on Land Surface Temperature over Cachar Region, Northeast India—A Case Study. *Sustainability* **2022**, *14*, 14087. [\[CrossRef\]](#)
8. Pathan, S.A.; Ashwini, K.; Sil, B.S. Spatio-Temporal Variation in Land Use/Land Cover Pattern and Channel Migration in Majuli River Island, India. *Environ. Monit. Assess.* **2021**, *193*, 811. [\[CrossRef\]](#)
9. Thakur, S.; Maity, D.; Mondal, I.; Basumatary, G.; Ghosh, P.B.; Das, P.; De, T.K. Assessment of Changes in Land Use, Land Cover, and Land Surface Temperature in the Mangrove Forest of Sundarbans, Northeast Coast of India. *Environ. Dev. Sustain.* **2021**, *23*, 1917–1943. [\[CrossRef\]](#)
10. Kafy, A.A.; Rahman, M.S.; Faisal, A.A.; Hasan, M.M.; Islam, M. Modelling Future Land Use Land Cover Changes and Their Impacts on Land Surface Temperatures in Rajshahi, Bangladesh. *Remote Sens. Appl. Soc. Environ.* **2020**, *18*, 100314. [\[CrossRef\]](#)
11. Ellwanger, J.H.; Kulmann-Leal, B.; Kaminski, V.L.; Valverde-Villegas, J.M.; Veiga, A.B.G.; Spilki, F.R.; Fearnside, P.M.; Caesar, L.; Giatti, L.L.; Wallau, G.L.; et al. Beyond Diversity Loss and Climate Change: Impacts of Amazon Deforestation on Infectious Diseases and Public Health. *An. Acad. Bras. Cienc.* **2020**, *92*, e20191375. [\[CrossRef\]](#)
12. Ganaie, T.A.; Jamal, S.; Ahmad, W.S. Changing Land Use/Land Cover Patterns and Growing Human Population in Wular Catchment of Kashmir Valley, India. *GeoJournal* **2021**, *86*, 1589–1606. [\[CrossRef\]](#)
13. Weber, C.; Puissant, A. Urbanization Pressure and Modeling of Urban Growth: Example of the Tunis Metropolitan Area. *Remote Sens. Environ.* **2003**, *86*, 341–352. [\[CrossRef\]](#)
14. Yamagata, Y.; Seya, H. Simulating a Future Smart City: An Integrated Land Use-Energy Model. *Appl. Energy* **2013**, *112*, 1466–1474. [\[CrossRef\]](#)
15. Tang, J.; Di, L.; Rahman, M.S.; Yu, Z. Spatial--Temporal Landscape Pattern Change under Rapid Urbanization. *J. Appl. Remote Sens.* **2019**, *13*, 024503. [\[CrossRef\]](#)
16. Shahfahad, S.T.; Mohd, R.; Hang, H.T.; Bhaskaran, S.; Rahman, A. Modelling Urban Heat Island (UHI) and Thermal Field Variation and Their Relationship with Land Use Indices over Delhi and Mumbai Metro Cities. *Environ. Dev. Sustain.* **2022**, *24*, 3762–3790. [\[CrossRef\]](#)
17. Rahaman, Z.A.; Kafy, A.-A.; Faisal, A.-A.; Al Rakib, A.; Jahir, D.M.A.; Fattah, M.A.; Kalaivani, S.; Rath, R.; Mallik, S.; Rahman, M.T. Predicting Microscale Land Use/Land Cover Changes Using Cellular Automata Algorithm on the Northwest Coast of Peninsular Malaysia. *Earth Syst. Environ.* **2022**, *6*, 817–835. [\[CrossRef\]](#)
18. Soltani, A.; Sharifi, E. Daily Variation of Urban Heat Island Effect and Its Correlations to Urban Greenery: A Case Study of Adelaide. *Front. Archit. Res.* **2017**, *6*, 529–538. [\[CrossRef\]](#)
19. Li, X.-X.; Koh, T.-Y.; Entekhabi, D.; Roth, M.; Panda, J.; Norford, L.K. A Multi-Resolution Ensemble Study of a Tropical Urban Environment and Its Interactions with the Background Regional Atmosphere. *J. Geophys. Res. Atmos.* **2013**, *118*, 9804–9818. [\[CrossRef\]](#)
20. Lim, T.K.; Rajabifard, A.; Khoo, V.; Sabri, S.; Chen, Y. The Smart City in Singapore: How Environmental and Geospatial Innovation Lead to Urban Livability and Environmental Sustainability. In *Smart Cities for Technological and Social Innovation*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 29–49.
21. Coates, L.; Haynes, K.; O'Brien, J.; McAneney, J.; de Oliveira, F.D. Exploring 167 Years of Vulnerability: An Examination of Extreme Heat Events in Australia 1844–2010. *Environ. Sci. Policy* **2014**, *42*, 33–44. [\[CrossRef\]](#)
22. Kleerekoper, L.; van Esch, M.; Salcedo, T.B. How to Make a City Climate-Proof, Addressing the Urban Heat Island Effect. *Resour. Conserv. Recycl.* **2012**, *64*, 30–38. [\[CrossRef\]](#)
23. Santamouris, M.; Haddad, S.; Saliari, M.; Vasilakopoulou, K.; Synnefa, A.; Paolini, R.; Ulpiani, G.; Garshasbi, S.; Fiorito, F. On the Energy Impact of Urban Heat Island in Sydney: Climate and Energy Potential of Mitigation Technologies. *Energy Build.* **2018**, *166*, 154–164. [\[CrossRef\]](#)

24. Santamouris, M. Recent Progress on Urban Overheating and Heat Island Research. Integrated Assessment of the Energy, Environmental, Vulnerability and Health Impact. Synergies with the Global Climate Change. *Energy Build.* **2020**, *207*, 109482. [[CrossRef](#)]
25. Hu, M.; Wang, Y.; Xia, B.; Huang, G. Surface Temperature Variations and Their Relationships with Land Cover in the Pearl River Delta. *Environ. Sci. Pollut. Res.* **2020**, *27*, 37614–37625. [[CrossRef](#)] [[PubMed](#)]
26. Almulhim, A.I.; Kafy, A.A.; Ferdous, M.N.; Fattah, M.A.; Morshed, S.R. Harnessing Urban Analytics and Machine Learning for Sustainable Urban Development: A Multidimensional Framework for Modeling Environmental Impacts of Urbanization in Saudi Arabia. *J. Environ. Manag.* **2024**, *357*, 120705. [[CrossRef](#)] [[PubMed](#)]
27. Zhang, X.; Estoque, R.C.; Murayama, Y. An Urban Heat Island Study in Nanchang City, China Based on Land Surface Temperature and Social-Ecological Variables. *Sustain. Cities Soc.* **2017**, *32*, 557–568. [[CrossRef](#)]
28. County, M. *Heat-Associated Deaths in Maricopa County, AZ—Multiyear Report for 2006–2013*; Maricopa County Department of Public Health: Phoenix, AZ, USA, 2019.
29. Iverson, S.A.; Gettel, A.; Bezold, C.P.; Goodin, K.; McKinney, B.; Sunenshine, R.; Berisha, V. Heat-Associated Mortality in a Hot Climate. *Public Health Rep.* **2020**, *135*, 631–639. [[CrossRef](#)] [[PubMed](#)]
30. Mendoza-Ponce, A.; Corona-Núñez, R.; Kraxner, F.; Leduc, S.; Patrizio, P. Identifying Effects of Land Use Cover Changes and Climate Change on Terrestrial Ecosystems and Carbon Stocks in Mexico. *Glob. Environ. Chang.* **2018**, *53*, 12–23. [[CrossRef](#)]
31. Tomlinson, C.J.; Chapman, L.; Thornes, J.E.; Baker, C.J. Including the Urban Heat Island in Spatial Heat Health Risk Assessment Strategies: A Case Study for Birmingham, UK. *Int. J. Health Geogr.* **2011**, *10*, 42. [[CrossRef](#)] [[PubMed](#)]
32. Sejati, A.W.; Buchori, I.; Rudiarto, I. The Spatio-Temporal Trends of Urban Growth and Surface Urban Heat Islands over Two Decades in the Semarang Metropolitan Region. *Sustain. Cities Soc.* **2019**, *46*, 101432. [[CrossRef](#)]
33. Lai, L.W.; Cheng, W.L. Urban Heat Island and Air Pollution—an Emerging Role for Hospital Respiratory Admissions in an Urban Area. *J. Environ. Health* **2010**, *72*, 32–35.
34. Ashwini, K.; Saw, G.K.; Singh, A. Phase Wise Spatial and Temporal Variations of Nitrogen Dioxide during and Pre COVID-19 Lockdown Period in Tier-1 Cities of India. *Spat. Inf. Res.* **2021**, *29*, 887–895. [[CrossRef](#)]
35. Saw, G.K.; Dey, S.; Kaushal, H.; Lal, K. Tracking NO₂ Emission from Thermal Power Plants in North India Using TROPOMI Data. *Atmos. Environ.* **2021**, *259*, 118514. [[CrossRef](#)]
36. Muduli, P.R.; Kumar, A.; Kanuri, V.V.; Mishra, D.R.; Acharya, P.; Saha, R.; Biswas, M.K.; Vidyarthi, A.K.; Sudhakar, A. Water Quality Assessment of the Ganges River during COVID-19 Lockdown. *Int. J. Environ. Sci. Technol.* **2021**, *18*, 1645–1652. [[CrossRef](#)] [[PubMed](#)]
37. Maithani, S.; Nautiyal, G.; Sharma, A. Investigating the Effect of Lockdown during COVID-19 on Land Surface Temperature: Study of Dehradun City, India. *J. Indian Soc. Remote Sens.* **2020**, *48*, 1297–1311. [[CrossRef](#)]
38. Kafy, A.-A.; Abdullah-Al-Faisal; Rahman, M.S.; Islam, M.; Al Rakib, A.; Islam, M.A.; Khan, M.H.H.; Sikdar, M.S.; Sarker, M.H.S.; Mawa, J.; et al. Prediction of Seasonal Urban Thermal Field Variance Index Using Machine Learning Algorithms in Cumilla, Bangladesh. *Sustain. Cities Soc.* **2021**, *64*, 102542. [[CrossRef](#)]
39. Abutaleb, K.; Ngie, A.; Darwish, A.; Ahmed, M.; Arafat, S.; Ahmed, F. Assessment of Urban Heat Island Using Remotely Sensed Imagery over Greater Cairo, Egypt. *Adv. Remote Sens.* **2015**, *04*, 35–47. [[CrossRef](#)]
40. Mandal, J.; Patel, P.P.; Samanta, S. Examining the Expansion of Urban Heat Island Effect in the Kolkata Metropolitan Area and Its Vicinity Using Multi-Temporal MODIS Satellite Data. *Adv. Sp. Res.* **2022**, *69*, 1960–1977. [[CrossRef](#)]
41. Zhou, W.; Qian, Y.; Li, X.; Li, W.; Han, L. Relationships between Land Cover and the Surface Urban Heat Island: Seasonal Variability and Effects of Spatial and Thematic Resolution of Land Cover Data on Predicting Land Surface Temperatures. *Landsc. Ecol.* **2014**, *29*, 153–167. [[CrossRef](#)]
42. Balogun, I.A.; Ishola, K.A. Projection of Future Changes in Landuse/Landcover Using Cellular Automata/Markov Model over Akure City, Nigeria. *J. Remote Sens. Technol.* **2017**, *5*, 22–31. [[CrossRef](#)]
43. Losiri, C.; Nagai, M.; Ninsawat, S.; Shrestha, R.P. Modeling Urban Expansion in Bangkok Metropolitan Region Using Demographic-Economic Data through Cellular Automata-Markov Chain and Multi-Layer Perceptron-Markov Chain Models. *Sustainability* **2016**, *8*, 686. [[CrossRef](#)]
44. Shatnawi, N.; Qdais, H.A. Mapping Urban Land Surface Temperature Using Remote Sensing Techniques and Artificial Neural Network Modelling. *Int. J. Remote Sens.* **2019**, *40*, 3968–3983. [[CrossRef](#)]
45. Wajahat, A.; Sil, S.B.; Ajay, G. Development of Rainfall-Runoff Model Using FFBPNN and LRNN for Silchar City—A Case Study. *Disaster Adv.* **2018**, *11*, 19–23.
46. Nath, H.; Adhikary, S.K.; Nath, S.; Kafy, A.-A.; Islam, A.R.M.T.; Alsulamy, S.; Khedher, K.M.; Shohan, A.A.A. Long-Term Trends and Spatial Variability in Rainfall in the Southeast Region of Bangladesh: Implication for Sustainable Water Resources Management. *Theor. Appl. Climatol.* **2024**, *155*, 3693–3717. [[CrossRef](#)]
47. Annayat, W.; Ashwini, K.; Sil, B.S. Monitoring Land Use and Land Cover Analysis of the Barak Basin Using Geospatial Techniques. In *Anthropogeomorphology: A Geospatial Technology Based Approach*; Springer International Publishing: Cham, Switzerland, 2022; pp. 427–441.
48. Annayat, W.; Sil, B.S. Assessing Channel Morphology and Prediction of Centerline Channel Migration of the Barak River Using Geospatial Techniques. *Bull. Eng. Geol. Environ.* **2020**, *79*, 5161–5183. [[CrossRef](#)]

49. Ashwini, K.; Pathan, S.A.; Sil, B.S. Delineation of Groundwater Potential Zone and Flood Risk Zone in Cachar District Area, India. *J. Water Eng. Manag.* **2020**, *1*, 16–34. [\[CrossRef\]](#)
50. Deb, S.; Sil, B.S. Climate Change Study for the Meteorological Variables in the Barak River Basin in North-East India. *Urban Clim.* **2019**, *30*, 100530. [\[CrossRef\]](#)
51. Annayat, W.; Sil, B.S. Changes in Morphometric Meander Parameters and Prediction of Meander Channel Migration for the Alluvial Part of the Barak River. *J. Geol. Soc. India* **2020**, *96*, 279–291. [\[CrossRef\]](#)
52. Office of the Registrar General & Census Commissioner Population Census 2011: Table C-16: Population by Mother Tongue, Assam; India, 2011. Available online: <https://censusindia.gov.in/nada/index.php/catalog/10195> (accessed on 1 November 2021).
53. Choudhury, M.; Jyethi, D.S.; Dutta, J.; Purkayastha, S.P.; Deb, D.; Das, R.; Roy, G.; Sen, T.; Bhattacharyya, K.G. Investigation of Groundwater and Soil Quality near to a Municipal Waste Disposal Site in Silchar, Assam, India. *Int. J. Energy Water Resour.* **2022**, *6*, 37–47. [\[CrossRef\]](#)
54. Robin; Kaur, P.; Kaur, J.; Bhat, S.A. Solid Waste Management: Challenges and Health Hazards. In *Recent Trends in Solid Waste Management*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 171–195.
55. Kumar, K.S.; Bhaskar, P.U.; Padmakumari, K. Estimation of Land Surface Temperature to Study Urban Heat Island Effect Using Landsat Etm+ Image. *Int. J. Eng. Sci. Technol.* **2012**, *4*, 771–778.
56. Scarano, M.; Sobrino, J.A. On the Relationship between the Sky View Factor and the Land Surface Temperature Derived by Landsat-8 Images in Bari, Italy. *Int. J. Remote Sens.* **2015**, *36*, 4820–4835. [\[CrossRef\]](#)
57. Rasul, A.; Balzter, H.; Smith, C. Spatial Variation of the Daytime Surface Urban Cool Island during the Dry Season in Erbil, Iraqi Kurdistan, from Landsat 8. *Urban Clim.* **2015**, *14*, 176–186. [\[CrossRef\]](#)
58. Gutman, G.; Huang, C.; Chander, G.; Noojipady, P.; Masek, J.G. Assessment of the NASA-USGS Global Land Survey (GLS) Datasets. *Remote Sens. Environ.* **2013**, *134*, 249–265. [\[CrossRef\]](#)
59. Roy, D.P.; Wulder, M.A.; Loveland, T.R.; Woodcock, C.E.; Allen, R.G.; Anderson, M.C.; Helder, D.; Irons, J.R.; Johnson, D.M.; Kennedy, R.; et al. Landsat-8: Science and Product Vision for Terrestrial Global Change Research. *Remote Sens. Environ.* **2014**, *145*, 154–172. [\[CrossRef\]](#)
60. Fu, P.; Weng, Q. Responses of Urban Heat Island in Atlanta to Different Land-Use Scenarios. *Theor. Appl. Climatol.* **2018**, *133*, 123–135. [\[CrossRef\]](#)
61. Yu, X.; Guo, X.; Wu, Z. Land Surface Temperature Retrieval from Landsat 8 TIRS-Comparison between Radiative Transfer Equation-Based Method, Split Window Algorithm and Single Channel Method. *Remote Sens.* **2014**, *6*, 9829–9852. [\[CrossRef\]](#)
62. Avdan, U.; Jovanovska, G. Algorithm for Automated Mapping of Land Surface Temperature Using LANDSAT 8 Satellite Data. *J. Sensors* **2016**, *2016*, 1480307. [\[CrossRef\]](#)
63. Liu, L.; Zhang, Y. Urban Heat Island Analysis Using the Landsat TM Data and ASTER Data: A Case Study in Hong Kong. *Remote Sens.* **2011**, *3*, 1535–1552. [\[CrossRef\]](#)
64. Guha, S.; Govil, H.; Dey, A.; Gill, N. Analytical Study of Land Surface Temperature with NDVI and NDBI Using Landsat 8 OLI and TIRS Data in Florence and Naples City, Italy. *Eur. J. Remote Sens.* **2018**, *51*, 667–678. [\[CrossRef\]](#)
65. Zhang, Y.; Yu, T.; Gu, X.; Zhang, Y.; Chen, L.; Yu, S.; Zhang, W.; Li, X. Land Surface Temperature Retrieval from CBERS-02 IRMSS Thermal Infrared Data and Its Applications in Quantitative Analysis of Urban Heat Island Effect. *Natl. Remote Sens. Bull.* **2006**, *10*, 789–797.
66. Khallef, B.; Biskri, Y.; Mouchara, N.; Brahamia, K. Analysis of Urban Heat Islands Using Landsat 8 OLI / TIR Data: Case of the City of Guelma (Algeria). *Asian J. Environ. Ecol.* **2020**, *12*, 42–51. [\[CrossRef\]](#)
67. Mansour, S.; Al-Belushi, M.; Al-Awadhi, T. Monitoring Land Use and Land Cover Changes in the Mountainous Cities of Oman Using GIS and CA-Markov Modelling Techniques. *Land Use Policy* **2020**, *91*, 104414. [\[CrossRef\]](#)
68. Ullah, S.; Ahmad, K.; Sajjad, R.U.; Abbasi, A.M.; Nazeer, A.; Tahir, A.A. Analysis and Simulation of Land Cover Changes and Their Impacts on Land Surface Temperature in a Lower Himalayan Region. *J. Environ. Manag.* **2019**, *245*, 348–357. [\[CrossRef\]](#) [\[PubMed\]](#)
69. Batty, M. Geocomputation Using Cellular Automata. In *Geocomputation*; Taylor & Francis: New York, NY, USA, 2000.
70. Hegde, N.P.; Muralikrishna, I.V.; Chalapatirao, K.V. Integration of Cellular Automata and Gis for Simulating Land Use Changes. In Proceedings of the 5th International Symposium on Spatial Data Quality SDQ 2007, Enschede, The Netherlands, 13–15 June 2007.
71. Bhardwaj, A.; Srivastava, H.S.; Singh, R.P. Evaluation of CartoDEM with the Ice, Cloud, and Land Elevation Satellite-2 and Global Ecosystem Dynamics Investigation Spaceborne LiDAR Datasets for Parts of Plain Region in Moga District, Punjab. *Environ. Sci. Proc.* **2024**, *29*, 73. [\[CrossRef\]](#)
72. Salim, M.Z.; Choudhari, N.; Kafy, A.-A.; Nath, H.; Alsulamy, S.; Rahaman, Z.A.; Aldosary, A.S.; Rahmand, M.T.; Al-Ramadan, B. A Comprehensive Review of Navigating Urbanization Induced Climate Change Complexities for Sustainable Groundwater Resources Management in the Indian Subcontinent. *Groundw. Sustain. Dev.* **2024**, *25*, 101115. [\[CrossRef\]](#)
73. Ahmad, M.; Khan, Z.; Anser, M.K.; Jabeen, G. Do Rural-Urban Migration and Industrial Agglomeration Mitigate the Environmental Degradation across China's Regional Development Levels? *Sustain. Prod. Consum.* **2021**, *27*, 679–697. [\[CrossRef\]](#)
74. Khanna, N.P. Urbanization and Urban Growth: Sustainable Cities for Safeguarding Our Future. In *Sustainable Cities and Communities*; Springer: Cham, Switzerland, 2020; pp. 953–965.
75. Guttikunda, S.K.; Nishadh, K.A.; Jawahar, P. Air Pollution Knowledge Assessments (APnA) for 20 Indian Cities. *Urban Clim.* **2019**, *27*, 124–141. [\[CrossRef\]](#)

76. Bilal, M.; Nichol, J.E.; Nazeer, M.; Shi, Y.; Wang, L.; Kumar, K.R.; Ho, H.C.; Mazhar, U.; Bleiweiss, M.P.; Qiu, Z.; et al. Characteristics of Fine Particulate Matter (PM_{2.5}) over Urban, Suburban, and Rural Areas of Hong Kong. *Atmosphere* **2019**, *10*, 496. [\[CrossRef\]](#)
77. Krittanawong, C.; Qadeer, Y.K.; Hayes, R.B.; Wang, Z.; Virani, S.; Thurston, G.D.; Lavie, C.J. PM_{2.5} and Cardiovascular Health Risks. *Curr. Probl. Cardiol.* **2023**, *48*, 101670. [\[CrossRef\]](#) [\[PubMed\]](#)
78. Makkonen, U.; Vestenius, M.; Huy, L.N.; Anh, N.T.N.; Linh, P.T.V.; Thuy, P.T.; Phuong, H.T.M.; Nguyen, H.; Thuy, L.T.; Aurela, M.; et al. Chemical Composition and Potential Sources of PM_{2.5} in Hanoi. *Atmos. Environ.* **2023**, *299*, 119650. [\[CrossRef\]](#)
79. Zhang, Q.; Li, Z.; Shen, Z.; Zhang, T.; Zhang, Y.; Sun, J.; Zeng, Y.; Xu, H.; Wang, Q.; Hang Ho, S.S.; et al. Source Profiles of Molecular Structure and Light Absorption of PM_{2.5} Brown Carbon from Residential Coal Combustion Emission in Northwestern China. *Environ. Pollut.* **2022**, *299*, 118866. [\[CrossRef\]](#)
80. Orru, H.; Olstrup, H.; Kukkonen, J.; López-Aparicio, S.; Segersson, D.; Geels, C.; Tamm, T.; Riikonen, K.; Maragkidou, A.; Sigsgaard, T.; et al. Health Impacts of PM_{2.5} Originating from Residential Wood Combustion in Four Nordic Cities. *BMC Public Health* **2022**, *22*, 1286. [\[CrossRef\]](#)
81. Abdelkareem, O.E.A.; Elamin, H.M.A.; Eltahir, M.E.S.; Adam, H.E.; Elhaja, M.E.; Rahamtalla, A.M.; Babatunde, O.; Elmar, C. Accuracy Assessment of Land Use Land Cover in Umabdalla Natural Reserved Forest, South Kordofan, Sudan. *Int. J. Agric. Environ. Sci.* **2018**, *3*, 5–9.
82. Faisal, A.-A.-; Kafy, A.-A.; Al Rakib, A.; Akter, K.S.; Jahir, D.M.A.; Sikdar, M.S.; Ashrafi, T.J.; Mallik, S.; Rahman, M.M. Assessing and Predicting Land Use/Land Cover, Land Surface Temperature and Urban Thermal Field Variance Index Using Landsat Imagery for Dhaka Metropolitan Area. *Environ. Chall.* **2021**, *4*, 100192. [\[CrossRef\]](#)
83. Sankarrao, L.; Ghose, D.K.; Rathinsamy, M. Predicting Land-Use Change: Intercomparison of Different Hybrid Machine Learning Models. *Environ. Model. Softw.* **2021**, *145*, 105207. [\[CrossRef\]](#)
84. Pontius, R.G. Quantification Error versus Location Error in Comparison of Categorical Maps. *Photogramm. Eng. Remote Sens.* **2000**, *66*, 1011–1016.
85. Landis, J.R.; Koch, G.G. An Application of Hierarchical Kappa-Type Statistics in the Assessment of Majority Agreement among Multiple Observers. *Biometrics* **1977**, *33*, 363–374. [\[CrossRef\]](#) [\[PubMed\]](#)
86. Arshad, S.; Ahmad, S.R.; Abbas, S.; Ashraf, A.; Siddiqui, N.A.; Islam, Z. ul Quantifying the Contribution of Diminishing Green Spaces and Urban Sprawl to Urban Heat Island Effect in a Rapidly Urbanizing Metropolitan City of Pakistan. *Land Use Policy* **2022**, *113*, 105874. [\[CrossRef\]](#)
87. Kafy, A.-A.; Faisal, A.-A.; Al Rakib, A.; Fattah, M.A.; Rahaman, Z.A.; Sattar, G.S. Impact of Vegetation Cover Loss on Surface Temperature and Carbon Emission in a Fastest-Growing City, Cumilla, Bangladesh. *Build. Environ.* **2022**, *208*, 108573. [\[CrossRef\]](#)
88. Afifa; Arshad, K.; Hussain, N.; Ashraf, M.H.; Saleem, M.Z. Air Pollution and Climate Change as Grand Challenges to Sustainability. *Sci. Total Environ.* **2024**, *928*, 172370. [\[CrossRef\]](#)
89. Cichowicz, R.; Bochenek, A.D. Assessing the Effects of Urban Heat Islands and Air Pollution on Human Quality of Life. *Anthropocene* **2024**, *46*, 100433. [\[CrossRef\]](#)
90. He, B.-J. Green Building: A Comprehensive Solution to Urban Heat. *Energy Build.* **2022**, *271*, 112306. [\[CrossRef\]](#)
91. Jabbar, H.K.; Hamoodi, M.N.; Al-Hameedawi, A.N. Urban Heat Islands: A Review of Contributing Factors, Effects and Data. *IOP Conf. Ser. Earth Environ. Sci.* **2023**, *1129*, 012038. [\[CrossRef\]](#)
92. Matte, T.; Lane, K.; Tipaldo, J.F.; Barnes, J.; Knowlton, K.; Torem, E.; Anand, G.; Yoon, L.; Marcotullio, P.; Balk, D.; et al. NPCC4: Climate Change and New York City's Health Risk. *Ann. N. Y. Acad. Sci.* **2024**, *early view*. [\[CrossRef\]](#)
93. Piracha, A.; Chaudhary, M.T. Urban Air Pollution, Urban Heat Island and Human Health: A Review of the Literature. *Sustainability* **2022**, *14*, 9234. [\[CrossRef\]](#)
94. Zewude, A.; Govindu, V.; Shibru, S.; Woldu, Z. Assessment of Spatiotemporal Dynamics of Land and Vegetation Cover Change Detection in Maze National Park, Southwest Ethiopia. *Environ. Monit. Assess.* **2022**, *194*, 460. [\[CrossRef\]](#) [\[PubMed\]](#)
95. Kafy, A.-A.; Saha, M.; Fattah, M.A.; Rahman, M.T.; Duti, B.M.; Rahaman, Z.A.; Bakshi, A.; Kalaivani, S.; Nafiz Rahaman, S.; Sattar, G.S. Integrating Forest Cover Change and Carbon Storage Dynamics: Leveraging Google Earth Engine and InVEST Model to Inform Conservation in Hilly Regions. *Ecol. Indic.* **2023**, *152*, 110374. [\[CrossRef\]](#)
96. Patra, S.; Sahoo, S.; Mishra, P.; Mahapatra, S.C. Impacts of Urbanization on Land Use /Cover Changes and Its Probable Implications on Local Climate and Groundwater Level. *J. Urban Manag.* **2018**, *7*, 70–84. [\[CrossRef\]](#)
97. Chadchan, J.; Shankar, R. Housing Preferences and Development Study in the Post LPG Era in India: A Case of Pune. *Int. J. Soc. Syst. Sci.* **2014**, *6*, 177. [\[CrossRef\]](#)
98. Chadchan, J.; Shankar, R. An Analysis of Urban Growth Trends in the Post-Economic Reforms Period in India. *Int. J. Sustain. Built Environ.* **2012**, *1*, 36–49. [\[CrossRef\]](#)
99. Yuan, S.; Ren, Z.; Shan, X.; Deng, Q.; Zhou, Z. Seasonal Different Effects of Land Cover on Urban Heat Island in Wuhan's Metropolitan Area. *Urban Clim.* **2023**, *49*, 101547. [\[CrossRef\]](#)
100. Zhang, S.; Yang, P.; Xia, J.; Wang, W.; Cai, W.; Chen, N.; Hu, S.; Luo, X.; Li, J.; Zhan, C. Land Use/Land Cover Prediction and Analysis of the Middle Reaches of the Yangtze River under Different Scenarios. *Sci. Total Environ.* **2022**, *833*, 155238. [\[CrossRef\]](#)
101. Maja, M.M.; Ayano, S.F. The Impact of Population Growth on Natural Resources and Farmers' Capacity to Adapt to Climate Change in Low-Income Countries. *Earth Syst. Environ.* **2021**, *5*, 271–283. [\[CrossRef\]](#)
102. Wijesekara, W.I.; Gokila, S.; Gomathi, T.; Prasad, S.; Deepa, M.; Sudha, P.N. New Opportunities and Future Prospects. In *Nanobiomaterials: Research Trends and Applications*; CRC Press: Boca Raton, FL, USA, 2023.

103. Hertog, S.; Gerland, P.; Wilmoth, J. India Overtakes China as the World's Most Populous Country. 2023. Available online: <https://www.un-ilibrary.org/content/papers/10.18356/27081990-153> (accessed on 1 November 2021).
104. UNDESA. 2014 Revision of the World Urbanization Prospects. 2014. Available online: <https://www.un.org/en/development/desa/publications/2014-revision-world-urbanization-prospects.html> (accessed on 1 November 2021).
105. Amiri, R.; Weng, Q.; Alimohammadi, A.; Alavipanah, S.K. Spatial–Temporal Dynamics of Land Surface Temperature in Relation to Fractional Vegetation Cover and Land Use/Cover in the Tabriz Urban Area, Iran. *Remote Sens. Environ.* **2009**, *113*, 2606–2617. [[CrossRef](#)]
106. Carlson, T.N.; Arthur, S.T. The Impact of Land Use—Land Cover Changes Due to Urbanization on Surface Microclimate and Hydrology: A Satellite Perspective. *Glob. Planet. Chang.* **2000**, *25*, 49–65. [[CrossRef](#)]
107. Mathew, A.; Sreekumar, S.; Khandelwal, S.; Kumar, R. Prediction of Land Surface Temperatures for Surface Urban Heat Island Assessment over Chandigarh City Using Support Vector Regression Model. *Sol. Energy* **2019**, *186*, 404–415. [[CrossRef](#)]
108. Derdouri, A.; Wang, R.; Murayama, Y.; Osaragi, T. Understanding the Links between LULC Changes and SUHI in Cities: Insights from Two-Decadal Studies (2001–2020). *Remote Sens.* **2021**, *13*, 3654. [[CrossRef](#)]
109. Rahman, M.N.; Rony, M.R.H.; Jannat, F.A.; Chandra Pal, S.; Islam, M.S.; Alam, E.; Islam, A.R.M.T. Impact of Urbanization on Urban Heat Island Intensity in Major Districts of Bangladesh Using Remote Sensing and Geo-Spatial Tools. *Climate* **2022**, *10*, 3. [[CrossRef](#)]
110. Barat, A.; Parth Sarthi, P. Characteristics of Remotely Sensed Urban Pollution Island (UPI) & Its Linkage with Surface Urban Heat Island (SUHI) over Eastern India. *Aerosol Sci. Eng.* **2023**, *7*, 220–236. [[CrossRef](#)]
111. Barat, A.; Parth Sarthi, P.; Kumar, S.; Kumar, P.; Sinha, A.K. Surface Urban Heat Island (SUHI) Over Riverside Cities along the Gangetic Plain of India. *Pure Appl. Geophys.* **2021**, *178*, 1477–1497. [[CrossRef](#)]
112. Shukla, A.; Jain, K. Analyzing the Impact of Changing Landscape Pattern and Dynamics on Land Surface Temperature in Lucknow City, India. *Urban For. Urban Green.* **2021**, *58*, 126877. [[CrossRef](#)]
113. Tripathy, P.; Kumar, A. Monitoring and Modelling Spatio-Temporal Urban Growth of Delhi Using Cellular Automata and Geoinformatics. *Cities* **2019**, *90*, 52–63. [[CrossRef](#)]
114. Basha, G.; Kishore, P.; Ratnam, M.V.; Jayaraman, A.; Agha Kouchak, A.; Ouarda, T.B.M.J.; Velicogna, I. Historical and Projected Surface Temperature over India during the 20th and 21st Century. *Sci. Rep.* **2017**, *7*, 2987. [[CrossRef](#)] [[PubMed](#)]
115. Benali, A.; Carvalho, A.C.; Nunes, J.P.; Carvalhais, N.; Santos, A. Estimating Air Surface Temperature in Portugal Using MODIS LST Data. *Remote Sens. Environ.* **2012**, *124*, 108–121. [[CrossRef](#)]
116. Abir, F.A.; Ahmmed, S.; Sarker, S.H.; Fahim, A.U. Thermal and Ecological Assessment Based on Land Surface Temperature and Quantifying Multivariate Controlling Factors in Bogura, Bangladesh. *Heliyon* **2021**, *7*, e08012. [[CrossRef](#)] [[PubMed](#)]
117. Das, T.; Das, S. Analysing the Role of Land Use and Land Cover Changes in Increasing Urban Heat Phenomenon in Chandannagar City, West Bengal, India. *J. Earth Syst. Sci.* **2022**, *131*, 261. [[CrossRef](#)]
118. Fadhil, M.; Hamoodi, M.N.; Ziboon, A.R.T. Mitigating Urban Heat Island Effects in Urban Environments: Strategies and Tools. *IOP Conf. Ser. Earth Environ. Sci.* **2023**, *1129*, 012025. [[CrossRef](#)]
119. Parida, B.R.; Bar, S.; Roberts, G.; Mandal, S.P.; Pandey, A.C.; Kumar, M.; Dash, J. Improvement in Air Quality and Its Impact on Land Surface Temperature in Major Urban Areas across India during the First Lockdown of the Pandemic. *Environ. Res.* **2021**, *199*, 111280. [[CrossRef](#)] [[PubMed](#)]
120. Parida, B.R.; Bar, S.; Kaskaoutis, D.; Pandey, A.C.; Polade, S.D.; Goswami, S. Impact of COVID-19 Induced Lockdown on Land Surface Temperature, Aerosol, and Urban Heat in Europe and North America. *Sustain. Cities Soc.* **2021**, *75*, 103336. [[CrossRef](#)] [[PubMed](#)]
121. Sahani, N.; Goswami, S.K.; Saha, A. The Impact of COVID-19 Induced Lockdown on the Changes of Air Quality and Land Surface Temperature in Kolkata City, India. *Spat. Inf. Res.* **2021**, *29*, 519–534. [[CrossRef](#)]
122. Mokarram, M.; Taripanah, F.; Minh Pham, T. Assessing Air Pollution Changes during the COVID-19 and Its Impact on the Urban Environment Using Remote Sensing and Neural Networks. *Adv. Sp. Res.* **2024**, *73*, 1760–1779. [[CrossRef](#)]
123. Irfeey, A.M.M.; Chau, H.-W.; Sumaiya, M.M.F.; Wai, C.Y.; Muttill, N.; Jamei, E. Sustainable Mitigation Strategies for Urban Heat Island Effects in Urban Areas. *Sustainability* **2023**, *15*, 10767. [[CrossRef](#)]
124. Mirabi, E.; Davies, P.J. A Systematic Review Investigating Linear Infrastructure Effects on Urban Heat Island (UHIULI) and Its Interaction with UHI Typologies. *Urban Clim.* **2022**, *45*, 101261. [[CrossRef](#)]
125. Karimi, A.; Mohammad, P.; García-Martínez, A.; Moreno-Rangel, D.; Gachkar, D.; Gachkar, S. New Developments and Future Challenges in Reducing and Controlling Heat Island Effect in Urban Areas. *Environ. Dev. Sustain.* **2023**, *25*, 10485–10531. [[CrossRef](#)]
126. Cevik Degerli, B.; Cetin, M. Evaluation of UTFVI Index Effect on Climate Change in Terms of Urbanization. *Environ. Sci. Pollut. Res.* **2023**, *30*, 75273–75280. [[CrossRef](#)] [[PubMed](#)]

127. Ribeiro, A.P.; Bollmann, H.A.; de Oliveira, A.; Rakauskas, F.; Cortese, T.T.P.; Rodrigues, M.S.C.; Quaresma, C.C.; Ferreira, M.L. The Role of Tree Landscape to Reduce Effects of Urban Heat Islands: A Study in Two Brazilian Cities. *Trees* **2023**, *37*, 17–30. [[CrossRef](#)]
128. Hassan, T.; Zhang, J.; Prodhan, F.A.; Pangali Sharma, T.P.; Bashir, B. Surface Urban Heat Islands Dynamics in Response to Lulc and Vegetation across South Asia (2000–2019). *Remote Sens.* **2021**, *13*, 3177. [[CrossRef](#)]

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