Chapter 7
Determining the Impact of Land Use and Land Cover on Microclimate with Reference to Thermal Variability in Srinagar Municipal Corporation

Mohd Saqib, Saleha Jamal, Manal Ahmad, Md Ashif Ali, Aakib Yaqoob Mir, and Md Babor Ali

Introduction

Urbanization is a complex and multifaceted process that involves the growth and expansion of cities and towns, driven by social, economic, and environmental factors. It is a global phenomenon that has accelerated in recent decades, especially in developing nations like India, where the urban population rose from 27.8% in 2001 to 34.0% in 2011 (Census of India, 2011a). This rapid urbanization has profound implications on local and regional climates, land use and land cover (LULC) patterns, and the well-being of urban residents. The urban heat island (UHI) phenomenon, which sees urban regions endure hotter temperatures than their rural surroundings, is one of the most significant climatic effects of urbanization. This effect has significant implications for energy consumption, air quality, and public health in urban areas. Higher temperatures in cities increase the demand for air conditioning, leading to higher energy consumption and greenhouse gas emissions (EPA, 2008). Further, warmer temperatures can make air pollution worse by encouraging the production of ground-level ozone and other secondary pollutants (Jacob & Winner, 2009). Also, this has direct and indirect impacts on public health, including heat-related illnesses, respiratory and cardiovascular diseases, and reduced overall well-being (Hajat et al., 2010). It is primarily attributed to changes in LULC, including the replacement of natural vegetation with built-up areas, that absorb and re-emit solar radiation more efficiently than natural landscapes, which alters the energy balance and increases the overall land surface temperature (LST) (Weng, 2009; Jamal et al., 2022). In addition, the reduction of vegetation in urban areas

M. Saqib · S. Jamal (✉) · M. Ahmad · M. A. Ali · A. Y. Mir · M. B. Ali
Department of Geography, Aligarh Muslim University, Aligarh, India

decreases evapotranspiration, a process that cools the surface by releasing water vapor into the atmosphere (Grimmond, 2007).

The assessment of LST and UHI effects in urban areas is crucial for understanding the climatic impacts of urbanization, urban planning, and environmental management. Remote sensing data provides a valuable tool for this purpose, offering large-scale and high-resolution data on LST and LULC (Weng, 2009). Several studies have used remote sensing data to assess the effect of LST and UHI on Indian cities, revealing a strong correlation between LST and LULC (Singh et al., 2018a, b, c; Kumar et al., 2018a, b). For instance, a study by Singh et al. (2018a, b, c) analyzed the UHI effect in Jaipur, India, using remote sensing data and found a strong relationship between LST and the normalized difference vegetation index (NDVI) and the normalized difference built-up index (NDBI). The study concluded that increasing vegetation cover and reducing built-up areas could help mitigate the UHI effect in Jaipur. Similarly, Kumar et al. (2018a, b) conducted a comparative study of the UHI effect in Delhi and Mumbai, two of India's largest cities, using remote sensing data. The study found that both cities experienced a significant UHI effect, with higher LST values in built-up areas compared to vegetated areas. The authors suggested that urban planning strategies, such as increasing green spaces and promoting sustainable building practices, could help reduce the UHI effect in these cities. Also, these studies highlight the importance of understanding the relationship between urbanization, LST, and the UHI effect in the context of rapidly urbanizing countries like India. By assessing the spatial and temporal variations of LST and its relationship with LULC, researchers and policymakers can develop targeted strategies to mitigate the UHI effect and its implications for energy consumption, air quality, and public health.

High Mountain Asia has undergone substantial warming recently, with the most pronounced increase in temperature observed in the Kashmir Himalayas over the past several years. This warming trend is anticipated to persist across the Himalayas (Bhutiyani et al., 2007). Changes in temperature will impact all facets of the Himalayan alpine ecosystems, comprised of hydrology and the cryosphere (Meraj et al., 2014; Murtaza & Romshoo, 2017; Marazi & Romshoo, 2018). Srinagar, located in the Kashmir Himalaya, is notably characterized by urban sprawl. The temperature in the city of Srinagar is 2–5 °C higher than in the countryside (Ackerman, 1985; Jiang & Tian, 2010). Because of the increased work prospects brought about by its socioeconomic center status, more individuals from rural areas are moving to the city in search of better amenities. The city's structure has been permanently altered as a result of this urban flux and unrestrained growth, which has also caused serious environmental and ecological damage (Jamal et al., 2023). Using ArcGIS, this study aims to assess how these land system changes affect the city's (especially in it is a municipal corporation) land surface temperatures. This tool allows for the analysis of large-scale geospatial data, providing a comprehensive view of the changes in land surface temperatures over time. In addition to this, the study also aims to establish a statistical relationship between land surface temperature (LST) and biophysical indices such as the normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), modified normalized

difference water index (MNDWI), normalized difference bareness index (NDBaI). These indices provide valuable insights into vegetation health, built-up, bareness and water content on the land surface. By correlating these indices with LST, the study hopes to gain a deeper understanding of how changes in vegetation and water content may influence the temperature variations in the city.

Database

This research has been conducted through geospatial satellite data. The satellite data were obtained from the USGS (United States Geological Survey) Earth Explorer (Table 7.1).

Methodology

Land Use and Land Cover Indices

Land use and land cover (LULC) indices are essential tools for monitoring and assessing changes in the Earth's surface, particularly in the context of urbanization, deforestation, and climate change. Among the widely used LULC indices are the normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI), normalized difference built-up index (NDBI), and normalized difference bareness index (NDBaI). These indices have been found to correlate with land surface temperature (LST), providing valuable insights into the relationships between land cover types and microclimatic conditions.

Normalized Difference Vegetation Index (NDVI)

The NDVI is a widely used index for assessing vegetation cover and monitoring vegetation dynamics (Rouse et al., 1974). It is calculated using Eq. (7.1):

Table 7.1 Geospatial data

Satellite	Sensor	Date	Resolution (m)	Path	Row	UTM zone
Landsat 7	Enhanced thematic mapper plus (ETM+)	29-08-2001	30	149	036	43
Landsat 5	Thematic mapper (TM)	01-08-2011	30	149	036	43
Landsat 8	Operational land imager (OLI)	12-08-2021	30	149	036	43

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{7.1}$$

Lower NDVI values suggest sparse or non-vegetated environments, while greater values indicate richer vegetation. Studies have shown a negative correlation between NDVI and LST, suggesting that increased vegetation cover can help mitigate urban heat island effects (Weng et al., 2004).

Modified Normalized Difference Water Index (MNDWI)

The MNDWI is an index used for mapping and monitoring water bodies (Xu, 2006). It is calculated using the difference between green (GREEN) and mid-infrared (MIR) reflectance values, normalized by their sum, which is given by Eq. (7.2):

$$MNDWI = \frac{(GREEN - MIR)}{(GREEN + MIR)} \tag{7.2}$$

Higher MNDWI values indicate the presence of water, while lower values represent non-water areas. The MNDWI has been found to correlate with LST, with water bodies generally exhibiting lower surface temperatures compared to surrounding land surfaces (Zhang et al., 2013).

Normalized Difference Built-Up Index (NDBI)

The NDBI is an index used for mapping and monitoring built-up areas (Zha et al., 2003). It is calculated using the difference between mid-infrared (MIR) and near-infrared (NIR) reflectance values, normalized by their sum, given by Eq. (7.3):

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \tag{7.3}$$

Built-up areas are represented by higher NDBI values, whereas undeveloped regions are represented by lower values. The urban heat island effect causes built-up regions to typically have higher surface temperatures, and studies have found a positive association between NDBI and LST (Weng et al., 2004).

Normalized Difference Bareness Index (NDBaI)

The NDBaI is an index used for mapping and monitoring bare soil and sparsely vegetated areas (Boschetti et al., 2008). It is calculated using Eq. (7.4):

$$NDBaI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \qquad (7.4)$$

Higher NDBaI values indicate bare soil or sparsely vegetated areas, while lower values represent non-bare areas. The NDBaI has been found to correlate with LST, with bare soil and sparsely vegetated areas generally exhibiting higher surface temperatures compared to vegetated areas (Boschetti et al., 2008).

The calculation of LULC indices, such as NDVI, MNDWI, NDBI, and NDBaI, provides valuable information on land cover types and their dynamics. These indices have been found to correlate with LST, offering insights into the relationships between land cover types and microclimatic conditions. Understanding these relationships is essential for creating effective land management strategies and mitigating the impacts of urbanization and climate change.

Retrieving of Land Surface Temperature from Landsat Data

Land surface temperature (LST) refers to the temperature of the surface of the Earth's land area (Abbas et al., 2021). It differs from air temperature and can be affected by factors such as vegetation, soil type, and urbanization. LST can be measured using remote sensing techniques, such as thermal infrared (TIR) imaging. It is an important variable in understanding and predicting weather patterns, studying land-atmosphere interactions, and exploring the effects of land-use changes on the climate.

In this study, the mono-window technique described by Qin et al. (2001) was used to obtain land surface temperature (LST) data from multiple Landsat satellite sensors over time. This method requires specific parameters, including ground emissivity, atmospheric transmittance, and effective mean atmospheric temperature. Initially, the original thermal infrared (TIR) bands, with resolutions of 100 meters for Landsat 8 OLI data and 120 meters for Landsat 5 TM data, were resampled to a 30-meter resolution by the USGS data center for subsequent analysis.

Calculation of LST from Thermal Band of Landsat 5 TM

Conversion of Digital Number (DN) to Top-of-Atmosphere (TOA) Spectral Radiance

To convert the spectral radiance of each thermal band into brightness temperature, Eq. (7.5) was used:

$$L_\lambda = \left(\frac{L\_\max\lambda - L\_\min\lambda}{\text{Qcal}\_\max - \text{Qcal}\_\min} \right) \times (\text{Qcal} - \text{Qcal}\_\min) + L\_\min\lambda \qquad (7.5)$$

Here, L_λ represents spectral radiance, while Qcal represents the quantized calibrated pixel value in DN. L_maxλ refers to spectral radiance scaled to Qcal_max (in Watts/m² × sr × μm), and L_minλ refers to spectral radiance scaled to Qcal_min.

Conversion of Radiance into Brightness Temperature and Land Surface Temperature

$$T = \frac{K2}{ln\left(\frac{K1}{L_\lambda} + 1\right)} - 273.15 \qquad (7.6)$$

Here, T represents the at-satellite brightness temperature; L_λ represents the top-of-atmosphere spectral radiance; and $K1$ and $K2$ are the constant values for the band being analyzed.

Calculation of LST from Thermal Band of Landsat 8 OLI

Conversion of Digital Number (DN) to Top-of-Atmosphere (TOA) Spectral Radiance

Initially, the Thermal Infrared Digital Numbers were converted to top-of-atmosphere (TOA) spectral radiance using the "radiance rescaling factor" proposed by Cohen (1960). This is calculated using Eq. (7.7) as:

$$L\lambda = ML \times Qcal + AL - Qi \qquad (7.7)$$

Here, $L\lambda$ represents TOA spectral radiance (in Watts/m^2 × sr × μm), ML represents the radiance multiplicative band, AL represents the radiance add band, Qcal represents the quantized and calibrated standard product pixel value (in DN), and Qi represents the correction value for Band 10, which is 0.29.

Conversion of Top-of-Atmosphere (TOA)/Spectral Radiance to Brightness Temperature

$$T = \frac{K2}{ln\left(\frac{K1}{L_\lambda} + 1\right)} \tag{7.8}$$

In Eq. (7.8), T refers to the at-satellite brightness temperature, L_λ refers to the top-of-atmosphere spectral radiance, and $K1$ and $K2$ are the constant values specific to the band being analyzed.

Proportion of Vegetation (PV)

It is calculated using Eq. (7.9):

$$PV = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \tag{7.9}$$

Land Surface Emissivity

NDVI (normalized difference vegetation index) is a characteristic of natural objects and is a crucial surface parameter derived from the radiance emitted by a specific location. The NDVI values are utilized to evaluate the average emissivity of an element present on the Earth's surface. The mathematical representation of this is given by Eq. (7.10):

$$E = 0.004 \times PV + 0.986 \tag{7.10}$$

Land Surface Temperature (LST)

The result of performing all the computations indicated above is the average temperature calculated from the object's observed brightness on Earth's surface. This is represented by Eq. (7.11):

$$LST = (BT/1) + W(BT/14280) * 1n(E) \tag{7.11}$$

The formula to compute the land surface temperature (LST) is given by Eq. (7.11), where LST is determined using the at-satellite brightness temperatures (BT) and the wavelength of emitted radiance (W). The equation also involves the natural logarithm of emissivity (E) and a constant value of 14,280 (Fig. 7.1).
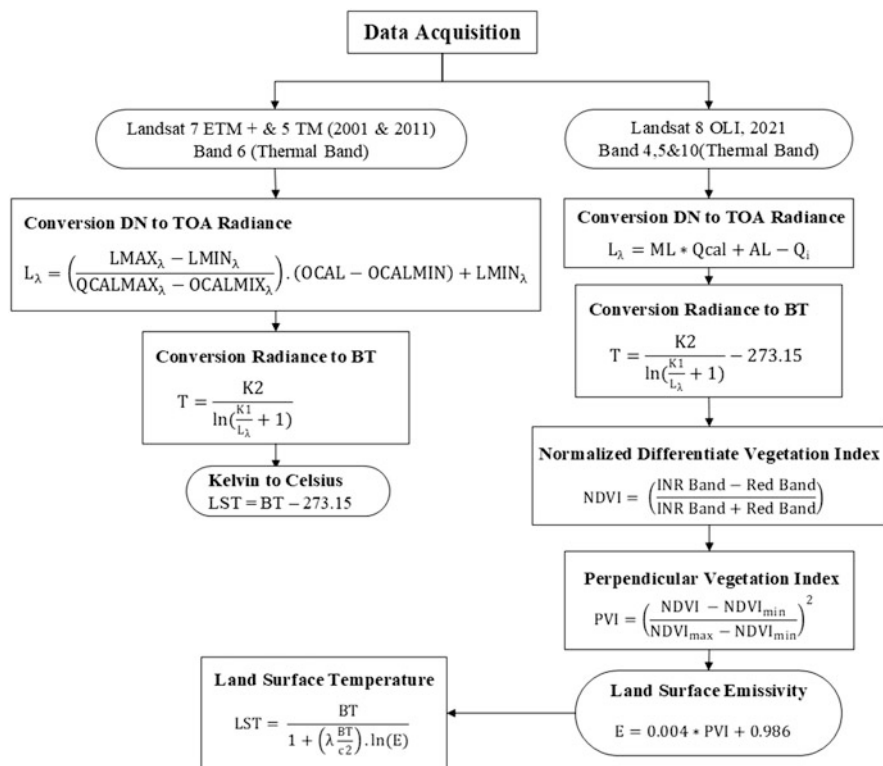

Fig. 7.1 Methodological flowchart for retrieving LST

Conversion of LST Data from Kelvin to Degree Celsius

Once all the five steps were completed, the LST data was obtained in Kelvin. Since this unit is not commonly used, the data was converted to the Celsius scale (°C) for ease of understanding. To get the result of LST in degree celcius, the formula i.e., C=(K-273.15) has been applied.

Statistical Tools

To explore the link between the indices of land use, land cover, and land surface temperature (LST), this study employs two statistical methods: Karl Pearson's correlation and simple linear regression. The methodology for each method is described below.

Karl Pearson's Correlation

Karl Pearson's correlation coefficient, also known as Pearson's *r*, is a measure of the linear relationship between two continuous variables (Pearson, 1895). In this study, Pearson's correlation is used to assess the strength and direction of the association between LST and LULC indices.

To calculate Pearson's correlation coefficient, Eq. (7.12) will be used:

$$r = \frac{\sum (X - \overline{X})(Y - \overline{Y})}{\sqrt{\sum (X - \overline{X})^2}\sqrt{(Y - \overline{Y})^2}} \tag{7.12}$$

Where, $\overline{X}$ = Mean of *X* Variables
$\overline{Y}$ = Mean of *Y* Variables

Simple Linear Regression

Simple linear regression is used to simulate the relationship between a dependent variable (in this case, LST) and an independent variable (in this case, LULC indices) (Montgomery et al., 2012). It seeks to identify the straight line that best captures the relationship between the two variables. The simple linear regression model can be represented as:

$$y = \beta 0 + \beta 1 x + \varepsilon \tag{7.13}$$

where y is the dependent variable (LST), x is the independent variable (LULC indices), β_0 is the intercept, β_1 is the slope, and ε is the error term (Montgomery et al., 2012).

To estimate the parameters β_0 and β_1, the method of least squares will be used, which minimizes the sum of the squared differences between the observed values and the predicted values of the dependent variable (Montgomery et al., 2012).

Once the regression model is estimated, the coefficient of determination (R^2) will be calculated to assess the proportion of the variance in LST that can be explained by the LULC indices. In addition, hypothesis tests will be conducted to determine the statistical significance of the estimated parameters.

Study Area: Srinagar Municipal Corporation

One of the largest cities in the Himalayas, Srinagar is situated in the Kashmir valley between 34°5′23′′ and 34°89′72′′ north latitude and 74°47′24′′ to 74°79′ east longitude at an altitude of around 1580–1595 meters (amsl) (Jamal & Ahmad, 2020). It is the summer capital of the Union Territory of Jammu and Kashmir, India, famous for its natural beauty, gardens, waterfronts, and houseboats (Kaul, 2011).

Srinagar Municipal Corporation (SMC) is the urban local body responsible for providing essential services and infrastructure to the city's residents. Established in 2000, the SMC is governed by the Jammu and Kashmir Municipal Corporation Act, 2000 (Government of Jammu and Kashmir, 2000). The corporation's jurisdiction covers an area of approximately 294 square kilometers, encompassing 74 municipal wards (SMC, 2021) (Fig. 7.2). The weather here is typically moderate throughout the summer, cool in the spring and fall, and frigid in the winter. The average mean minimum temperature is 7.29 °C, while the average mean maximum temperature is 19.27 °C. The wintertime lows are below zero, and the summertime highs reach 38 °C. The Valley receives 84 cm of rain annually on average (Shafiq et al., 2022). The city's population, as per the 2011 Census, was 1,273,312, with a population density of 4313 persons per square kilometer (Census of India, 2011a, b). It has a diverse population, comprising various ethnic and religious groups, including Kashmiri Muslims, Kashmiri Pandits, and Sikhs. The city's economy is primarily driven by tourism, handicrafts, and agriculture, particularly horticulture (Kaul, 2011). Due to the considerable expansion of transport, tourism, economic, and other networked amenities, the size of the Srinagar Municipal Corporation as well as its population have increased. The main issues that have been explored in this area include urban planning and development, solid waste management, sanitation, public health, and disaster management due to which the city is facing several challenges such as unplanned urbanization, inadequate infrastructure, environmental degradation, and temperature rise which have implications on the quality of life of its residents (Bhat & Rather, 2017).
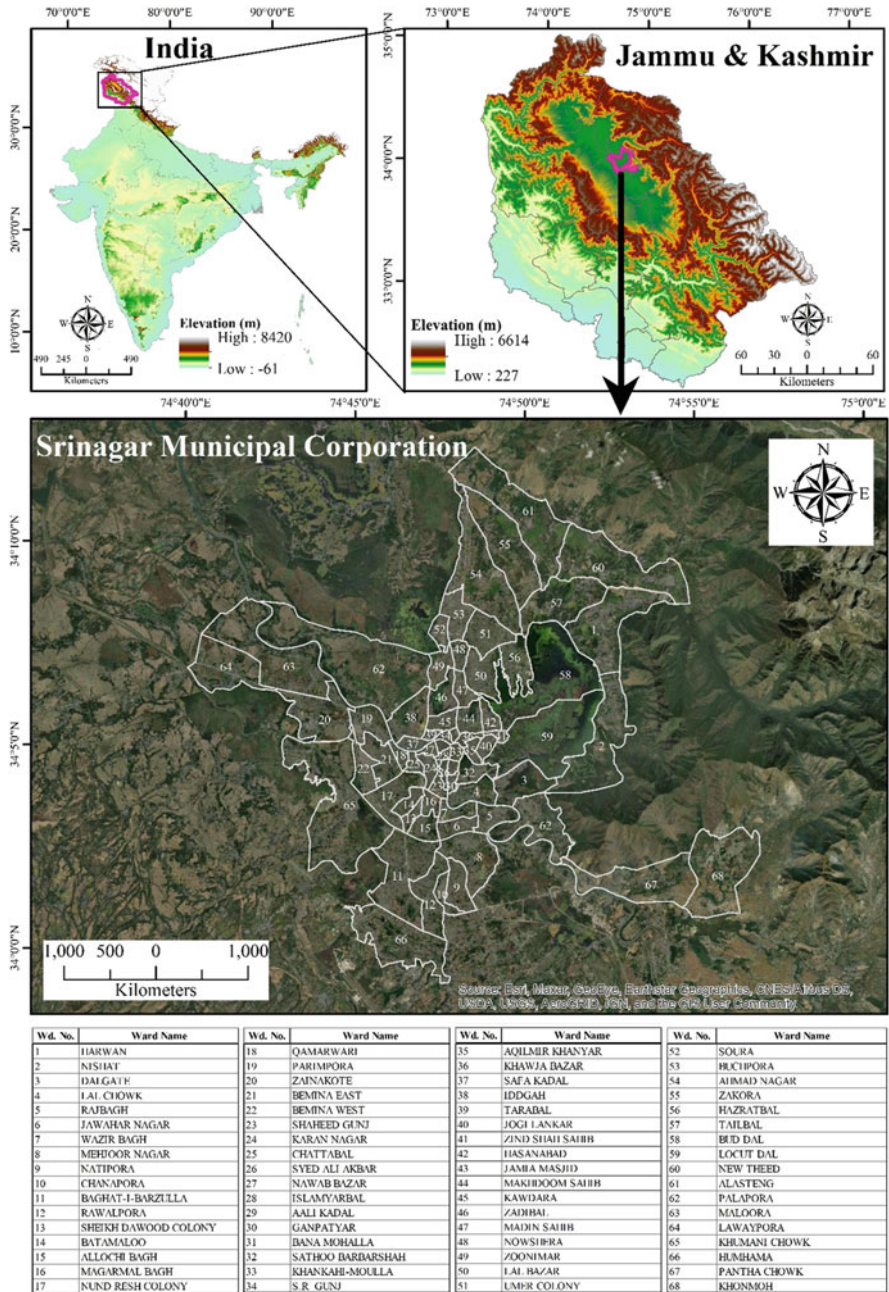
Wd. No.	Ward Name	Wd. No.	Ward Name	Wd. No.	Ward Name	Wd. No.	Ward Name
1	HARWAN	18	QAMARWARI	35	AQILMIR KHANYAR	52	SOURA
2	NISHAT	19	PARIMPORA	36	KHAWJA BAZAR	53	BUCHPORA
3	DALGATE	20	ZAINAKOTE	37	SAFA KADAL	54	AHMAD NAGAR
4	LAL CHOWK	21	BEMINA EAST	38	IDDGAH	55	ZAKORA
5	RAJBAGH	22	BEMINA WEST	39	TARABAL	56	HAZRATBAL
6	JAWAHAR NAGAR	23	SHAHEED GUNJ	40	JOGI LANKAR	57	TAILBAL
7	WAZIR BAGH	24	KARAN NAGAR	41	ZIND SHAH SAHB	58	BUD DAL
8	MEHJOOR NAGAR	25	CHATTABAL	42	HASANABAD	59	LOCUT DAL
9	NATIPORA	26	SYED ALI AKBAR	43	JAMIA MASJID	60	NEW THEED
10	CHANAPORA	27	NAWAB BAZAR	44	MAKHDOOM SAHB	61	ALASTENG
11	BAGHAT-I-BARZULLA	28	ISLAMYARBAL	45	KAWDARA	62	PALAPORA
12	RAWALPORA	29	AALI KADAL	46	ZADIBAL	63	MALDOORA
13	SHEIKH DAWOOD COLONY	30	GANPATYAR	47	MADIN SAHB	64	LAWAYPORA
14	BATAMALOO	31	BANA MOHALLA	48	NOWSHERA	65	KHUMANI CHOWK
15	ALLOCHI BAGH	32	SATHOO BARBARSHAH	49	ZOONIMAR	66	HUMHAMA
16	MAGARMAL BAGH	33	KHANKAHI-MOULLA	50	LAL BAZAR	67	PANTHA CHOWK
17	NUND RESH COLONY	34	S.R. GUNJ	51	UMER COLONY	68	KHONMOH

Fig. 7.2 Study area: Srinagar Municipal Corporation

Results and Discussion

Normalized Difference Vegetation Index (NDVI)

The normalized difference vegetation index (NDVI) is a widely used remote sensing technique for assessing and monitoring vegetation health and density. In Fig. 7.3, we have analyzed the NDVI values for the Srinagar Municipal Corporation (SMC) area for the years 2001, 2011, and 2021.

The results indicate a significant change in the NDVI values over the two-decade period. The minimum NDVI values show an increasing trend, rising from −0.49 in 2001 to −0.12 in 2021. This suggests a reduction in non-vegetated or barren areas, which could be attributed to urban expansion, land-use changes, or reclamation of previously degraded lands.

On the other hand, the maximum NDVI values exhibit a fluctuating pattern, with an increase from 0.46 in 2001 to 0.71 in 2011, followed by a decrease to 0.61 in 2021. The increase in the maximum NDVI value between 2001 and 2011 may be indicative of improved vegetation health and density, possibly due to favorable climatic conditions, afforestation efforts, or better agricultural practices. However, the subsequent decline in the maximum NDVI value in 2021 could be a result of factors such as urbanization, land conversion for infrastructure development, or environmental stressors like climate change and pollution.

These findings highlight the dynamic nature of the SMC's vegetation cover over the years. The observed changes in NDVI values can have a big impact on the sustainability, ecology, and environment of the city. It is essential for policymakers and urban planners to consider these trends while formulating strategies for land-use planning, resource management, and environmental conservation in the SMC area.
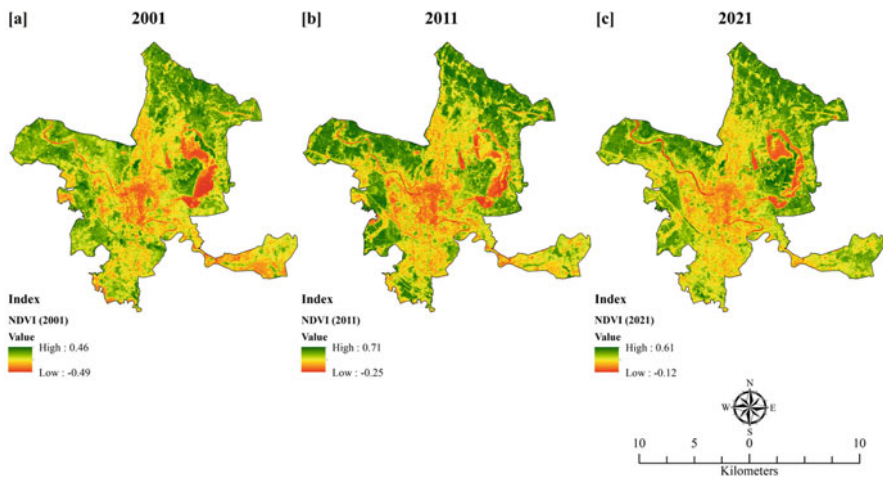

Fig. 7.3 Normalized deference vegetation index (NDVI) of Srinagar Municipal Corporation: (**a**) 2001, (**b**) 2011 and (**c**) 2021

Further research could involve a more in-depth analysis of the factors contributing to the observed NDVI changes, as well as the potential impacts on the city's ecosystem services, such as water regulation, air purification, and carbon sequestration. Future studies could explore the relationship between NDVI trends and socioeconomic factors, such as population growth, urbanization, and economic development, to better understand the drivers of vegetation change in the SMC area.

Modified Normalized Difference Water Index (MNDWI)

The modified normalized difference water index (MNDWI) is a widely used remote sensing technique for mapping and monitoring water bodies (Xu, 2006). In this study, we analyze the MNDWI values for Srinagar Municipal Corporation (SMC) for the years 2001, 2011, and 2021, focusing on the changes in minimum and maximum MNDWI values over time (Fig. 7.4).

The MNDWI values for SMC in 2001, 2011, and 2021 show considerable variation. In 2001, the minimum MNDWI value was -0.34, while the maximum value was 0.61. By 2011, the minimum MNDWI value had decreased to -0.62, and the maximum value had also decreased to 0.55. In 2021, the minimum MNDWI value increased slightly to -0.39, but the maximum value decreased further to 0.26.

The decreasing trend in maximum MNDWI values from 2001 to 2021 suggests a reduction in the extent and quality of water bodies within SMC (Xu, 2006). This could be attributed to factors such as urbanization, land reclamation, and pollution, which have been known to negatively impact water bodies (Seto et al., 2012). The fluctuation in minimum MNDWI values may indicate changes in land cover types,
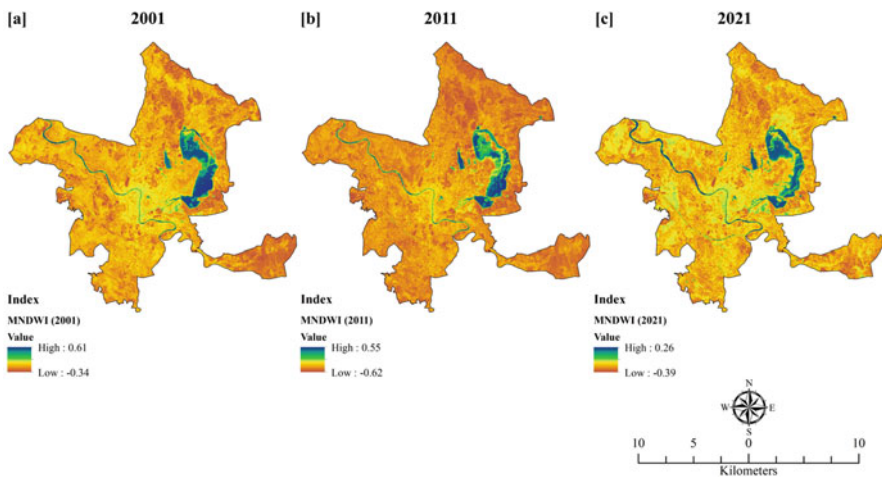

Fig. 7.4 Modified normalized deference water index (MNDWI) of Srinagar Municipal Corporation: (**a**) 2001, (**b**) 2011, and (**c**) 2021

such as an increase in impervious surfaces or vegetation, which can affect the MNDWI calculations (McFeeters, 1996).

The analysis of MNDWI values for SMC from 2001 to 2021 highlights the potential changes in water bodies over time. Further study is required to determine the root cause of these changes and to create effective management plans for safeguarding and enhancing the region's water resources.

Normalized Difference Built-Up Index (NDBI)

Figure 7.5 shows a decrease in the high NDBI values from 0.48 in 2001 to 0.22 in 2021, indicating a reduction in the extent or density of built-up areas over the 20-year period. This could be attributed to various factors such as urban planning policies, land-use changes, or economic factors affecting the growth of built-up areas.

On the other hand, the low NDBI values show a more complex trend. The value decreased from -0.31 in 2001 to -0.52 in 2011, suggesting an increase in non-built-up areas such as vegetation or water bodies. However, the value increased to -0.40 in 2021, indicating a possible decrease in non-built-up areas compared to 2011. This could be due to changes in land-use patterns, such as the transformation of agricultural land to built-up areas or the loss of vegetation due to natural or human-induced factors. Overall, the NDBI value for SMC suggests a decrease in built-up areas and a fluctuating trend in non-built-up areas over the 20-year period.
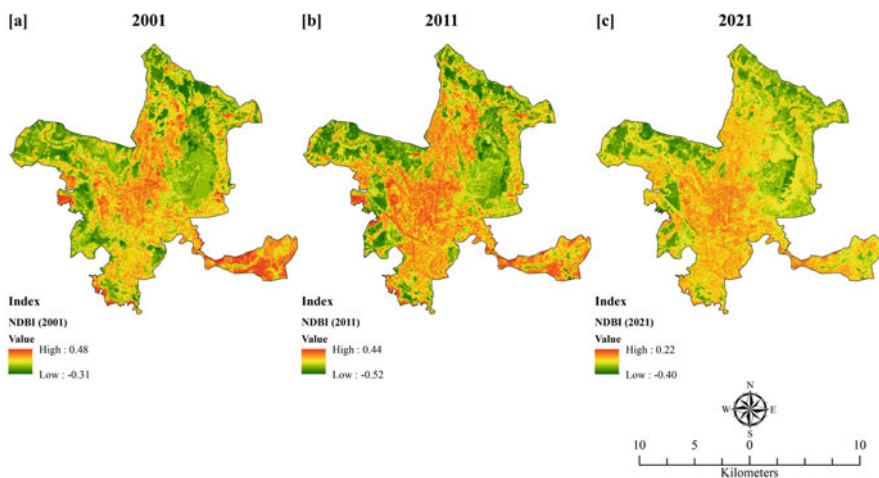

Fig. 7.5 Normalized deference built-up index (NDBI) of Srinagar Municipal Corporation: (**a**) 2001, (**b**) 2011, and (**c**) 2021

Normalized Difference Bareness Index (NDBaI)

Based on the provided NDBaI data for Srinagar MC, Fig. 7.6 shows a decrease in the high NDBaI values from 0.29 in 2001 to −0.03 in 2021, indicating a reduction in the extent or density of bare land areas over the 20-year period. This could be attributed to various factors such as land-use changes, reforestation efforts, or urban expansion.

On the other hand, the low NDBaI values show an increase from −0.81 in 2001 to −0.89 in 2011, suggesting a decrease in bare land areas and an increase in non-bare land areas such as vegetation or built-up areas. However, the value increased to −0.67 in 2021, indicating a possible increase in bare land areas compared to 2011. This could be due to changes in land-use patterns, such as the conversion of vegetation or built-up areas to bare land, or the loss of vegetation due to natural or human-induced factors. The NDBaI data for SMC suggests a decrease in bare land areas and a fluctuating trend in non-bare land areas over the 20-year period.

Land Surface Temperature (LST)

The data in Table 7.2 shows the Land Surface Temperature (LST) statistics for the Srinagar Municipal Corporation area for the years 2001, 2011, and 2021 (Fig. 7.7). The statistics include minimum temperature, temperature, mean temperature, standard deviation, and coefficient of variation.

Minimum Temperature The minimum LST has increased slightly over the years, from 17.75 °C in 2001 to 17.93 °C in 2011, and further to 18.10 °C in 2021. This
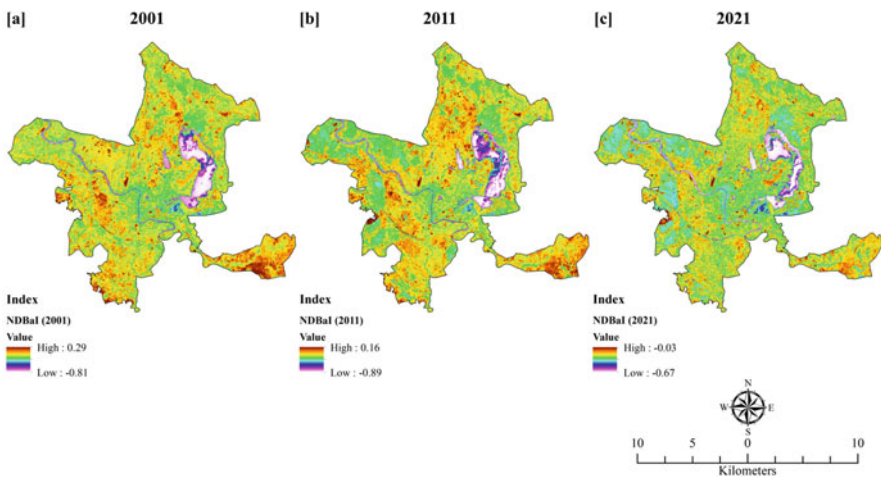

Fig. 7.6 Normalized deference bareness index (NDBaI) of Srinagar Municipal Corporation: (**a**) 2001, (**b**) 2011, and (**c**) 2021

Table 7.2 LST statistics (2001–2021)

Years	Minimum temperature (°C)	Maximum temperature (°C)	Mean temperature (°C)	Standard deviation	Coefficient of variation
2001	17.75	33.34	22.46	2.602	11.585
2011	17.93	33.72	23.02	2.571	11.169
2021	18.10	34.36	24.42	2.880	11.794
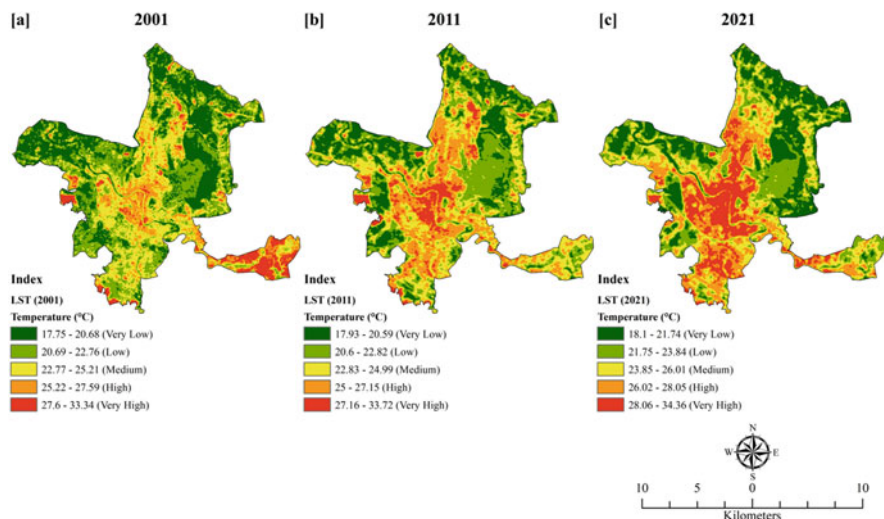
Fig. 7.7 Land surface temperature of Srinagar Municipal Corporation: (**a**) 2001, (**b**) 2011, and (**c**) 2021

indicates an increase in the lowest surface temperatures in the Srinagar Municipal Corporation area over the two decades.

Maximum Temperature The maximum LST has also increased over the years, from 33.34 °C in 2001 to 33.72 °C in 2011, and further to 34.36 °C in 2021. This suggests a consistent increase in the highest surface in the region over the 20-year period.

Mean Temperature The mean LST has increased consistently over the years, from 22.46 °C in 2001 to 23.02 °C in 2011, and further to 24.42 °C in 2021. This indicates a general warming trend in the Srinagar Municipal Corporation area over the two decades.

Standard Deviation The standard deviation, which measures the dispersion of LST values, has remained relatively stable over the years, with a slight increase from 2.602 in 2001 to 2.571 in 2011, and then a more noticeable increase to 2.880 in 2021. This suggests that the variability in surface temperatures has increased slightly over the 20-year period.

Coefficient of Variation The coefficient of variation, which measures the relative variability of LST values, has also remained relatively stable over the years, with values of 11.585 in 2001, 11.169 in 2011, and 11.794 in 2021. This indicates that the relative variability in surface temperatures has not changed significantly over the two decades.

The data reveals a general warming trend in the Srinagar Municipal Corporation area over the two decades, with an increase in minimum, maximum, and mean LST values. The variability in surface temperatures has remained relatively stable, with a slight increase in standard deviation and a relatively constant coefficient of variation. These findings have important implications for urban planning, public health, and environmental sustainability in the Srinagar Municipal Corporation area.

Area Under Different LST Categories

Figure 7.8 depicts the distribution of land surface temperature (LST) classes in the Srinagar Municipal Corporation area for the years 2001, 2011, and 2021. The corresponding data is provided in Table 7.3:

1. *Very Low LST:* The area with very low LST has decreased from 67.13 km (27.36%) in 2001 to 46.73 km (19.05%) in 2011, and then increased to
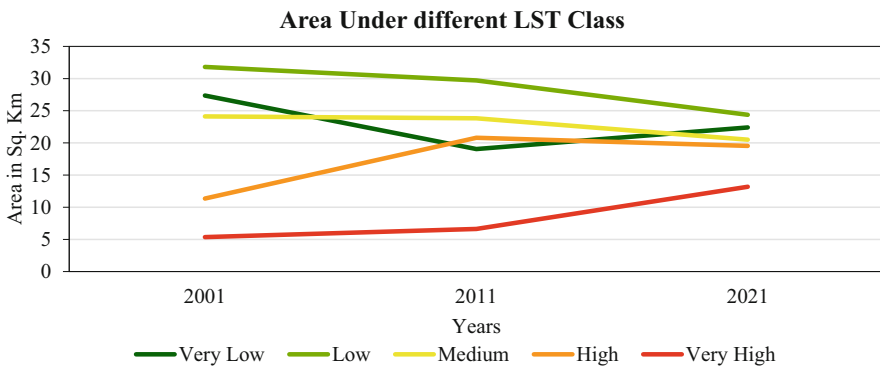

Fig. 7.8 Area under different LST categories (2001–2021)

Table 7.3 Area under different LST categories (2001–2021)

LST class	2001		2011		2021	
	Area (km)	Area (%)	Area (km)	Area (%)	Area (km)	Area (%)
Very low	67.13	27.36	46.73	19.05	54.98	22.41
Low	78.05	31.81	72.90	29.71	59.79	24.37
Medium	59.18	24.12	58.45	23.82	50.30	20.50
High	27.85	11.35	51.03	20.80	47.93	19.53
Very high	13.14	5.36	16.24	6.62	32.35	13.18

Table 7.4 Karl Pearson's coefficient of correlation between LST and LULC indices

Year	NDVI & LST	MNDWI & LST	NDBI & LST	NDBaI & LST
2001	−0.552	−0.358	0.862	0.491
2011	−0.638	−0.181	0.846	0.476
2021	−0.539	−0.283	0.783	0.407

    54.98 km (22.41%) in 2021. This indicates a reduction in the extent of areas with the lowest surface temperatures over the two decades, with a slight recovery between 2011 and 2021.

2. *Low LST:* The area with low LST has also decreased from 78.05 km (31.81%) in 2001 to 72.90 km (29.71%) in 2011, and further to 59.79 km (24.37%) in 2021. This suggests a consistent decline in the extent of areas with low surface temperatures over the 20-year period.

3. *Medium LST:* The area with medium LST has remained relatively stable, with a slight decrease from 59.18 km (24.12%) in 2001 to 58.45 km (23.82%) in 2011, and then a more noticeable decrease to 50.30 km (20.50%) in 2021. This indicates a modest decline in the extent of areas with medium surface temperatures over the two decades.

4. *High LST:* The area with high LST has increased significantly from 27.85 km (11.35%) in 2001 to 51.03 km (20.80%) in 2011, and then slightly decreased to 47.93 km (19.53%) in 2021. This suggests a substantial increase in the extent of areas with high surface temperatures between 2001 and 2011, with a minor decline between 2011 and 2021.

5. *Very High LST:* The area with very high LST has increased from 13.14 km (5.36%) in 2001 to 16.24 km (6.62%) in 2011, and then more than doubled to 32.35 km (13.18%) in 2021. This indicates a consistent increase in the extent of areas with the highest surface temperatures over the 20-year period.

    The data reveals a general trend of decreasing areas with very low and low LST, and increasing areas with high and very high LST in the Srinagar Municipal Corporation area over the two decades. This raises the possibility of a rise in surface temperatures in the area, which may be brought on by land cover changes, urbanization, and the urban heat island effect, among other things. These findings have important implications for urban planning, public health, and environmental sustainability in the Srinagar Municipal Corporation area.

    The data provided in Table 7.4 shows the correlation between various vegetation and water indices (NDVI, MNDWI, NDBI, and NDBaI) and land surface temperature (LST) for the years 2001, 2011, and 2021. Figure 7.9 shows the simple linear regression analysis between LST and LULC indices (i.e., NDVI, MNDWI, NDBI, and NDBaI).

1. *NDVI & LST*: The negative correlation between NDVI (normalized difference vegetation index) and LST indicates that as vegetation cover increases, LST decreases. This is consistent with the cooling effect of vegetation due to shading
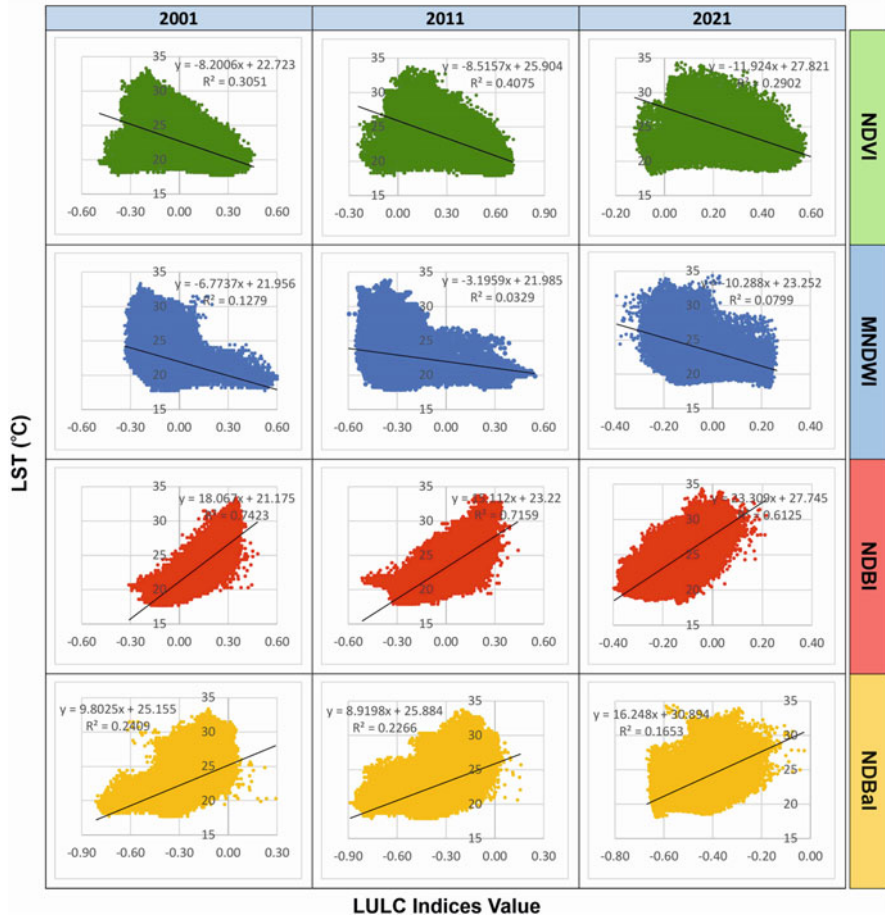
Fig. 7.9 Simple linear regression analysis between LST and LULC indices (i.e., NDVI, MNDWI, NDBI, and NDBaI)

and evapotranspiration. The correlation has become slightly less negative from −0.552 in 2001 to −0.539 in 2021, suggesting a possible decrease in the cooling effect of vegetation over time. Similarly, the regression value also shows a decreasing trend from 0.3051 to 0.2902 during 2001–2021.

2. *MNDWI & LST*: The negative correlation between MNDWI (modified normalized difference water index) and LST implies that as the presence of water bodies increases, LST decreases. This is in line with the cooling effect of water bodies due to their heat-absorbing and storing properties. The correlation has become less negative from −0.358 in 2001 to −0.283 in 2021, indicating a potential decrease in the cooling effect of water bodies over time. Also, the regression value decreased from 0.1279 to 0.0799 in 2001–2021.
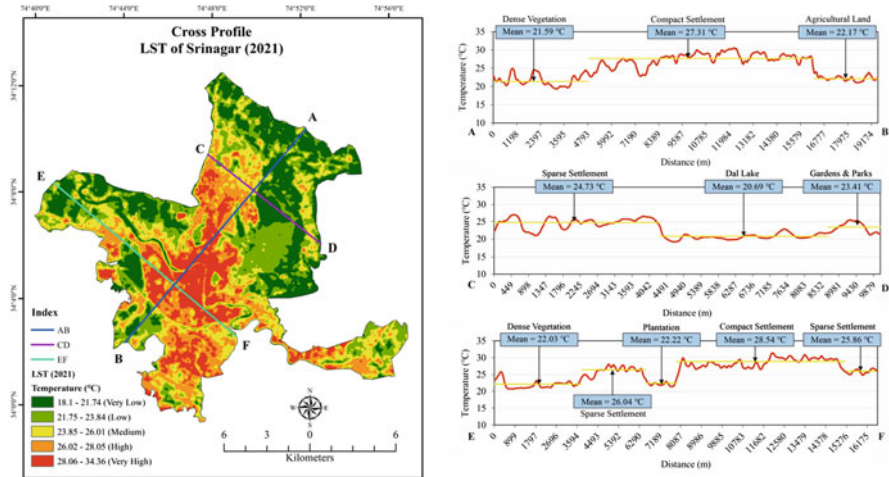
Fig. 7.10 Cross profile of land surface temperature (2021)

3. *NDBI & LST*: The positive correlation between NDBI (normalized difference built-up index) and LST suggests that as built-up areas increase, LST also increases. This is consistent with the urban heat island effect, where impervious surfaces and built-up areas contribute to higher surface temperatures. The correlation has slightly decreased from 0.862 in 2001 to 0.783 in 2021, which may indicate a reduction in the impact of built-up areas on LST over time. Consequently, the r^2 value also decreased from 0.7423 in 2001 to 0.6125 in 2021.

4. *NDBaI & LST*: The positive correlation between NDBaI (normalized difference bareness index) and LST indicates that as bare land areas increase, LST also increases. This is in line with the fact that bare land areas, with little to no vegetation or water bodies, tend to have higher surface temperatures. The correlation has decreased from 0.491 in 2001 to 0.407 in 2021, suggesting a possible reduction in the impact of bare land areas on LST over time. Hence, the linear regression value also decreased from 0.2409 to 0.1653 during the specified period.

The data shows that vegetation and water bodies have a cooling effect on LST, while built-up and bare land areas contribute to higher surface temperatures. Over the years, the correlations between these indices and LST have changed, indicating potential shifts in the impacts of land cover types on LST. Urban planners and policymakers can utilize this information to come up with plans to lessen the impact of urban heat islands and increase thermal comfort in cities.

Figure 7.10 shows the analysis of the data of three cross profiles of land surface temperature (LST) in SMC that reveal distinct patterns in LST values across different land cover types.

Cross Profile 1 (AB) shows that dense vegetation has a mean LST of 21.59 °C, which is significantly lower than the mean LST of 27.31 °C observed in compact
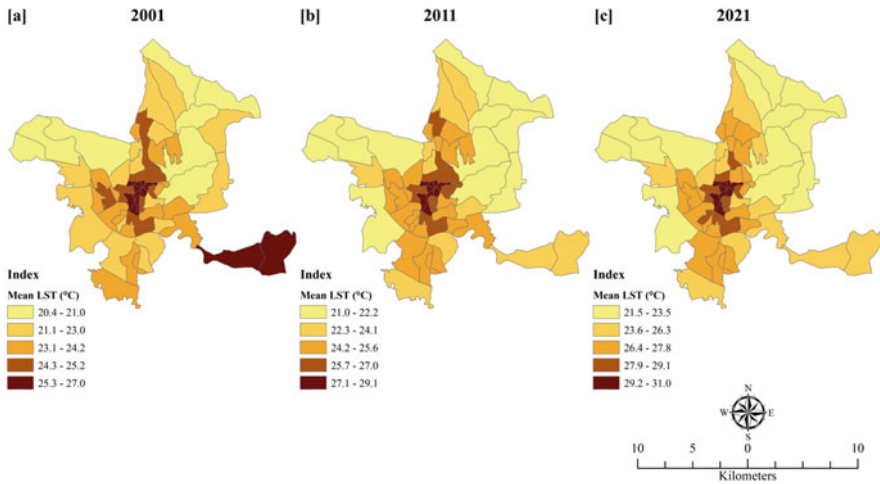
Fig. 7.11 Ward-wise LST of Srinagar Municipal Corporation: (**a**) 2001, (**b**) 2011, and (**c**) 2021

settlements. This difference can be attributed to the cooling effect of vegetation, which provides shade and promotes evapotranspiration, thereby reducing surface temperatures. Agricultural land, with a mean LST of 22.17 °C, also exhibits lower temperatures compared to compact settlements, likely due to the presence of vegetation and moisture in the soil.

Cross Profile 2 (CD) presents a different pattern, with sparse settlements having a mean LST of 24.73 °C, which is higher than the 20.69 °C observed for Dal Lake. This can be explained by the water body's ability to absorb and store heat, resulting in lower surface temperatures. Parks and gardens, with a mean LST of 23.41 °C, also exhibit lower temperatures compared to sparse settlements, highlighting the cooling effect of green spaces in urban areas.

Cross Profile 3 (EF) demonstrates a complex pattern of LST values across various land cover types. Dense vegetation has a mean LST of 22.03 °C, while sparse settlements have mean LST values of 26.04 °C and 25.86 °C. The lower temperature in dense vegetation can be attributed to the cooling effect of vegetation, as mentioned earlier. Plantations, with a mean LST of 22.22 °C, also exhibit lower temperatures, likely due to the presence of vegetation and moisture. Compact settlements, however, have the highest mean LST of 28.54 °C, indicating the strong influence of impervious surfaces and built-up areas on surface temperatures.

As a result, interpreting data of the three cross profiles of LST in SMC highlights the significant role of land cover types in influencing surface temperatures. Vegetation, water bodies, and green spaces tend to have lower LST values, while compact and sparse settlements exhibit higher temperatures. These results highlight the significance of including green areas and vegetation in urban planning to reduce the urban heat island effect and enhance thermal comfort in urban areas.

Based on the land surface temperature data of various wards in Srinagar, the following observations can be made (Fig. 7.11):

- Wards in city centers, like Khwaja Bazar, Karan Nagar, Nawab Bazar, Shaheed Gunj, Islam Yarbal, and Safa Kadal, have the highest land surface temperatures. This is likely due to higher concentration of built-up area and less vegetation in these wards.
- Wards with more open spaces, parks, and vegetation, like Hazratbal, Idgah, and Rajourikadal, have comparatively lower land surface temperatures.
- Wards on the city periphery, like Hyderpora, Bemina, and Parimpora, show land surface temperatures between 31 and 33 °C. Though less built up, these wards also have lesser vegetation.
- Wards, like Pantha Chowk and Khonmoh, lying too far from the city center, were earlier covered with bare land and had extremely high temperatures in 2001; but with the advent of time, these lands were converted for other land-use activities and thus temperature showed a slight decrease in 2011 and 2021.
- The ward-wise mean LST during the decades 2001 and 2021 showed a continuous increase from 25.3 °C to 31 °C in the areas having the maximum LST, while the mean LST increased from 20.4 °C to 23.5 °C in the areas having the minimum LST.

Recommendations

Based on the analysis, the following recommendations can be made to reduce urban heat effect:

- Increase green cover and urban forestry. Plant more trees along roads, parks, and other open spaces.
- Use cool and reflective materials for rooftops and pavements to reduce heat absorption.
- Adopt urban planning measures like increasing open spaces and water bodies to lower land surface temperatures.

Implement technology-based solutions like cool roofs, cool pavements, and urban canopies to combat urban heat.

Conclusion

The study has provided valuable insights into the spatial and temporal variations of land surface temperature (LST) in Srinagar Municipal Corporation (SMC) using remote sensing data from Landsat 7, Landsat 5, and Landsat 8 for the years 2001, 2011, and 2021, respectively. The analysis has demonstrated the significant influence of land use and land cover, vegetation cover, and urban morphology on LST, in line with previous research (Li et al., 2019; Singh et al., 2018a, b, c). It has contributed to the growing body of research on LST and urban heat island effects in rapidly urbanizing areas, especially in SMC, by highlighting the main areas and

wards having the maximum and minimum LST. It has become increasingly susceptible to the negative effects of climate change and environmental degradation due to its uncontrolled urban growth and rapid population increase, which have disrupted the ecological services and hydrological procedures in the city. The study also showed that the lowest land surface temperature (LST) was in bodies of water and places with vegetation cover, while the highest LST was found in built-up areas and visible rock formations. The study also discovered a negative association between the NDVI and MNDWI indices for vegetation and water bodies and the land surface temperature. The pursuit of the Sustainable Development Goals (SDGs) by 2030 may be threatened by the continued trend of urban growth over the past several decades that has the potential to cause a catastrophic environmental imbalance. The use of remote sensing data has proven to be a valuable tool for assessing LST and its spatial and temporal variations, providing critical information for urban planning, environmental management, and public health initiatives.

The study's result has an important significance for SMC's urban planning and environmental management. By understanding the factors that contribute to higher LST and the urban heat island effect, policymakers and urban planners can develop strategies to mitigate these effects, such as increasing green spaces, promoting sustainable urban design, and implementing energy-efficient building practices. Furthermore, the results can inform public health initiatives aimed at reducing heat-related illnesses and improving overall well-being in urban areas. However, further research is needed on more detailed studies of the factors influencing LST in SMC, including the role of small-scale urban elements, such as construction supplies and street geometry. In addition, the potential effects of the urban heat island on local climate, quality of the air, and human health warrant further investigation. Long-term monitoring of LST and urban development in SMC is essential to assess the effectiveness of mitigation strategies and inform adaptive management approaches.

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