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Research Article

A study on temporal Land surface temperature (LST) and its relationship with Remote sensing ecological spectral indices of Agra and Aizawl Cities in India

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Abstract
Rapid urbanisation reshapes the natural and cultural landscape, increasing the local climate, particularly Land Surface Temperature (LST). Understanding the LST characteristics, their influence on Urban Heat Island (UHI), and their relationship with the ecological indices is crucial for sustainable urban and environmental planning. This study investigated a principle of growing concern over rapid urbanisation and its impact urban climate and LST through remote sensing ecological spectral indices in the urban landscapes of Agra and Aizawl, India, from 2014 to 2023. The study utilizes the data from the United State Geological Survey (USGS) Landsat series (Landsat 5 and 8), employing the thermal infrared (TIR) bands to calculate LST.The study incorporates remote sensing spectral indices to examine their correlation with LST, providing an adequate understanding of UHI and its relationship with the environment. Linear and polynomial regression models were also employed to analyze temperature trends and fluctuations. The results showed a negative correlation between LST and Normalized Difference Vegetation Index (NDVI), while a positive correlation between LST and Normalized Difference Built-up Index (NDBI). And it also observed a slight increase in LST for both cities, with significant year-to-year variations. The decrease in LST was observed in 2020, which can be attributed to reduced human activities during the COVID-19 pandemic lockdown. These study results enhance the comprehension of urban thermal behaviour and the consequences of urbanization on the environment. The utilization of geospatial technologies proves indispensable in assessing LST and its implications, paving the way for future research to enhance urban resilience and sustainability.

Keywords: Agra, Aizawl, Ecological Spectral Indices, Land Surface Temperature (LST), Remote Sensing

INTRODUCTION

Land Surface Temperature (LST) is integral to Earth's energy equilibrium and environmental processes, serving as a key parameter in remote sensing and climate studies. It provides valuable insights into the thermal characteristics of the Earth's surface, which is essential for monitoring climate change, understanding urban heat islands (Guha *et al.,* 2018; Grover and Singh, 2015), and comprehending ecosystem dynamics. This exploration into LST delves into its significance, measurement methods, and broader implications for climate science and environmental monitoring. The escalating urbanization has brought about Land Use and Land Cover (LULC) fluctuations, notably impacting LST (Saha *et al*., 2024). The release of heat from settlements, vehicles, and industry primarily contributes Urban Heat Island (UHI) phenomenon (Chakraborty *et al.,* 2014). In the era of rapid development, our surroundings have undergone transformation and degradation, reflecting climatic and atmospheric changes as a central theme in the 21st century, focusing on climate change and environmental degradation (Mustafa *et al.,* 2020; Kikon *et al.,* 2023). Climate change, global warming, and local climate fluctuations influence Earth's surface energy budget by many types of human activities, such as the increasing utilization of artificial materials to cover additional land areas. (Sanjan *et al.,* 2023, Ramachandra *et al.,* 2012). The study of LST serves as a directional examination of climate trends, considering factors, although not entirely human-induced. LST is a vital climate variable, impacting the planetary boundary layer's global energy distribution and the atmosphere's general thermal condition (Jin and Liang, 2006).

Geospatial technology emerged as an effective tool for assessing LST and its impact on various Earth surface phenomena. (John *et al.,* 2020; Dickinson,1995; Hussain *et al.,* 2023). Thermal infrared (TIR) sensors in remote sensing provide quantitative surface temperature information across land cover categories (Mallick *et al.,* 2008; Mathew *et al.,* 2017). The ground's radiative surface temperature, as determined by the infrared spectrum, is known as LST. (Li *et al.,* 2013). This temperature plays a fundamental role in terrestrial thermal behavior, influencing the temperature that the Earth's surface radiates (Talukdar, 2020). An accessible definition is how hot the Earth's "surface" could sense at a certain point if touched (European Space Agency). As a measure of change in the climate and a regulator of vertical land radiation, LST has a major impact on the earth's surface processes. (Frey and Kuenzer, 2014). This control, in turn, affects Terrestrial and latent heat flows interchange with the atmosphere. (Aires *et al*., 2001). Geographical research and writing have traditionally focused on three main concepts: environment, space, and place. While the emphasis on each concept has varied, GIS applications have predominantly fallen within the environmental category (Johnston, 2006). LST is a crucial parameter in fields such as hydrology, climatology, and geophysics (Bechtel, 2015). India's rise in the number of towns and urban population between 1901 and 2001 indicates a significant increase, resulting in environmental challenges on land, water, air pollution, noise, and dumping waste issues (Uttara *et al.,* 2012).

Agra, one of India's oldest and fastest-growing cities, has encountered challenges related to urbanization. Despite developing in an unplanned manner, Aizawl experiences fewer environmental problems due to urbanization (Vanlalchhuanga *et al*., 2022). Keeping this in view, the present study aimed to analyse LST between 2013 and 2022 in Agra and Aizawl cities in India. The study highlights the adverse effects of unplanned urbanization, emphasizing the need for environmentally friendly development in developing states. Furthermore, the study addresses the research gap regarding the environmental impact of COVID-19 pandemic lockdown in two distinct socio-cultural regions of India.

MATERIALS AND METHODS

Study area

The capital city of Mizoram, in India, is Aizawl, situated between longitudes 92°40'E and 92°47'E and latitudes 23°39'45" N and 23°50'39" N. According to the 2011 census data Aizawl had a population of 293,416, representing 26.89% of the state population. The gender distribution was almost equal, with females accounting for 50.61% and males 49.39% of the residents. Aizawl falls under the climate category of Monsoon influenced humid sub-tropical climates (Cwa) as per the Köppen climate classification system, characterized by mild winters and hot, humid summers. Covering an area of 120.25 kilometers. The city's unplanned growth and its climate raised environmental issues such as changes in LST and Urban Heat Island UHI effects. In Aizawl, finding a balance between preserving spaces while accommodating expansion remains essential for sustainable progress.

Agra is located on the banks of Yamuna River, located between 27°10'36''N latitudes and 78°0'29''E longitudes (Fig. 1). According to the 2011 census, Agra has a population of 1,585,704, with males constituting 53percent and females 47% of the total population. The literacy rate in Agra is 73%, and the city has a sex ratio of 875 females per thousand males. Covering an area of 550.121 square kilometers, Agra is significantly larger than Aizawl in terms of geographical area and population. Being an ancient city, Agra is renowned for its historical and cultural significance, and it is home to the iconic Taj Mahal and several other historical monuments. Comparing these two cities provides valuable insights into how varying geographical and socio-economic contexts influence UHI and environmental challenges.

Land Surface Temperature (LST) calculation

For calculating the LST, Landsat series (Landsat 5 and 8) data were utilized between 2014 and 2023; Landsat 8 has 2 thermal bands (band 10 and 11) with specific thermal infrared wavelength band 10 has 10.60-11.19 μm while band 11 had 11.50-12.51 μm wavelength while Landsat 5 had one thermal band, band 6 with a wavelength between 10.40-12.5 micrometers. Because of the increased calibration uncertainty related to band 11, it was advised to utilize data from band 10 (Guha *et al*., 2018). Dark Object Subtract 1 (DOS1) atmospheric correction was applied at the preprocessing stage and to examine the LST, Landsat data were preprocessed in Qgis, and the following mono-algorithm by Qin *et al*. (2001) was used:

Conversion of Thermal infrared pixel number to Top of Atmosphere (TOA) radiance

$$L\lambda = ML * Qcal + AL - O_i \qquad \text{Eq. 1}$$

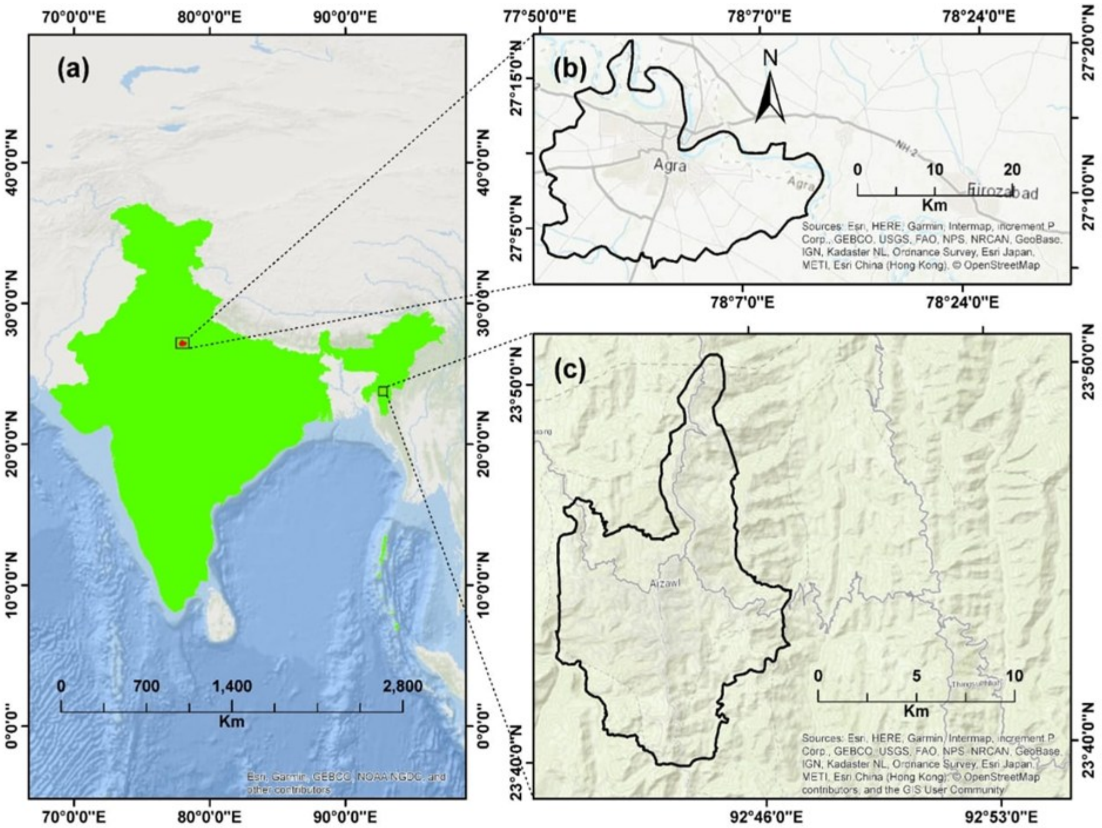


Fig.1. *Location of the study area showing Agra and Aizawl city boundary map*

Where,
$L\lambda$ = Top of Atmosphere Spectral Radiance
ML = multiplicative rescaling factor of a specific band
Qcal = quantized and calibrated standard product pixel values (DN)
AL = Additive rescaling factor of a specific band
O_i = is the band correction for thermal band CH_4
Conversion of TOA to Brightness Temperature (BT)

$$BT = K2 / \ln (K1/ L\lambda + 1) – 273.15 \quad \text{Eq. 2}$$

Where,
BT= TOA brightness temperature $L\lambda$ = TOA spectral radiance
K_1 = Thermal conversion constants for specific bands
K_2 = Thermal conversion constants for specific bands"
Proportion of Vegetation (P_v)

$$P_V = NDVI – NDVI_{min} / NDVI_{max} – NDVI_{min} \quad \text{Eq. 3}$$

Where,
$NDVI_{min}$ = Minimum Dn values from NDVI
$NDVI_{max}$ = Maximum Dn values from NDVI
For determining the NDVI the following equation was "used

$$NDVI = NIR – Red / NIR + Red \quad \text{Eq. 4}$$

Land Surface Emissivity (LSE)

$$E = 0.004 * P_V + 0.986 \quad \text{Eq. 5}$$

Where,
Pv = Proportion of Vegetation
0.986 = correction value of the equation
0.04= standard deviation of 49 soil spectral
Land Surface Temperature

$$LST = BT / (1+ (\lambda * BT/ C_2) *I_nE)) \quad \text{Eq. 6}$$

For studying" the LST's correlation with spectral indices, the correlation coefficient, computed by utilizing Karl Pearson's method, evaluated the direction and magnitude of linear relationship among the 2 variables, where "r" can vary from -1 to 1. A positive 'r' number depicts a positive correlation, whereas a negative 'r' proposes a negative correlation, and an 'r' value close to 0 implies a weak or no linear correlation. The Karl Pearson's correlation coefficient (r) is given as follows:

$$r = \sum dxdy \sqrt{\sum dx2}\sqrt{\sum dy2} \quad \text{Eq. 7}$$

Regression analysis

Linear regression and polynomial regression were used to study the patterns and trends of LST. Linear regression is employed to study the trends in LST over Aizawl and Agra city, and this method provides the slope, intercept, R-squared Value and P-value for each temperature class (Max, Mean, Min) whereas, Polynomial regression with a degree of 3 is used to analyze the non-linear trends and fluctuation in the data. This method provides the coefficients of polynomial and R-squared.

Spectral indices

A combination of spectral reflectance at multiple wavelengths to represent the proportional number of the things of interest are called spectral indices, and it was calculated using the formula provided by the United

States Geological Survey (Masek *et al.,* 2006, Vermote *et al.,* 2016). To calculate the correlation coefficient between LST and the spectral indices, the fishnet tools in Arcmap were utilized to extract the pixel value, and then. pixel pair-wise correlation was established using Excel. The following formulae were used.

For "Normalized Difference Vegetation Index calculation:

NDVI = (NIR - Red) / (NIR + Red) Eq. 8

For Normalized Difference Built-Up Index calculation:

NDBI = (SWIR1 - NIR) / (SWIR1 + NIR) Eq. 9

For Normalized Difference Moisture Index calculation:

NDMI = ((NIR - SWIR1) / (NIR + SWIR1)) Eq. 10

For Normalized Difference Bareness Index calculation*:*

NDBaI = ((SWIR1 - TIR) / (SWIR1 + TIR)) Eq. 11

For Bare Soil Index calculation:

BSI = ((Red+SWIR) - (NIR+Blue)) / ((Red+SWIR) + (NIR+Blue)") Eq. 12

RESULTS AND DISCUSSION

Pre-monsoon LST Aizawl

The Linear regression pre-Monsoon LST of Aizawl data (Table 1) indicated a slope of 0.44, indicating a slight rise in the surface temperature. During the study years, the intercept had a value of 29.23, which showed the estimated maximum temperature in the reference year. the R^2 has a value of 0.112, which showed that only 11.2 percent of the variability in the temperature is explained by the model. The P-value of 0.319 depicted that this trend is not statistically significant, reflecting small level if increasing LST during the pre-monsoon period in Aizawl. For mean temperature, the linear regression slope was -0.020, showing a slightly decreasing trend, the intercept was 22.15 and the R^2value was 0.085, indicating that the linear model explained only 8.5% of the variability, the P-Value of 0.379 also showed that this trend was not statistically significant, this slight decrease in mean LST, could have indicated variability influenced by other factors, the minimum temperature showed a slope of -0.016 with an intercept of 15.67with the R-squared value of 0.050, and the P-value was 0.495, which suggested that a very slight decrease in minimum temperature.

The Polynomial regression with a degree of 3 is also employed to study the non-linear trends of LST. For the pre-monsoon maximum temperature, the R-squared value has 0.471, which is a much better fit than the linear regression model, capturing significant fluctuation and dips in certain years. For example, the polynomial model showed a decrease in temperature in 2018 and a slight increase in 2020. Mean temperature had an R-squared value of 0.402. This model also depicted the fluctuation and notable dips in 2016 and 2019, with a slight increase in 2020. This indicated that that mean temperatures varied significantly from year to year. The minimum temperature polynomial regression model had an R^2 value of 0.361; this model indicated fluctuations with dips in years like 2017 and 2019, followed by a slight rise in 2020. This suggested that minimum temperatures have also experienced notable year-to-year variability (Fig. 2 and 3).

Pre-Monsoon Land surface temperature Agra

For Agra city, the linear regression analysis of pre-monsoon maximum temperature showed increasing trends. The intercept is 36.17 with an R2 value of 0.157 and the P-value of 0.238, showing a slightly increasing trend in maximum LST, the mean temperature had a slope of 0.032 with an intercept value of 31.28, and the R2 value is 0.188 with a P-value of 0.194 showing that the trend was not statistically significant but also suggested a small rise in mean LST. Minimum LST analysis results showed that the slope of 0.026 with an intercept of 25.56. The R-squared value is 0.221 and the P-value is 0.153, depicting that the trend was not significant but also indicated a slight increase in minimum temperatures.

The polynomial regression analysis of maximum LST has an R-squared value of 0.521, which showed a good fit and fluctuation. Indicating that maximum temperature had also differed from year to year. Mean temperature has polynomial R-squared value of 0.492 with dips and fluctuations in 2016 and 2019 with a minimum rise in 2020, this suggested that a complex interaction influ-

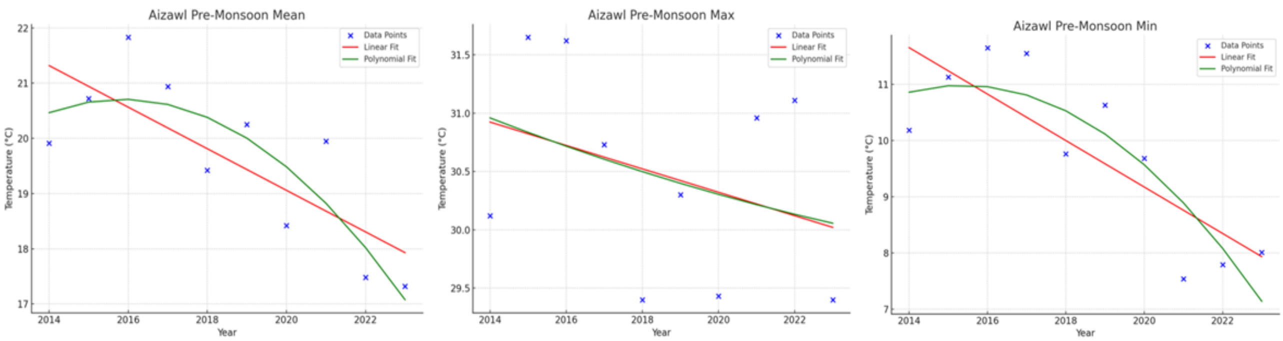


Fig. 2. *Aizawl Pre-Monsoon regression charts showing surface temperature (Max, Mean, Min)*

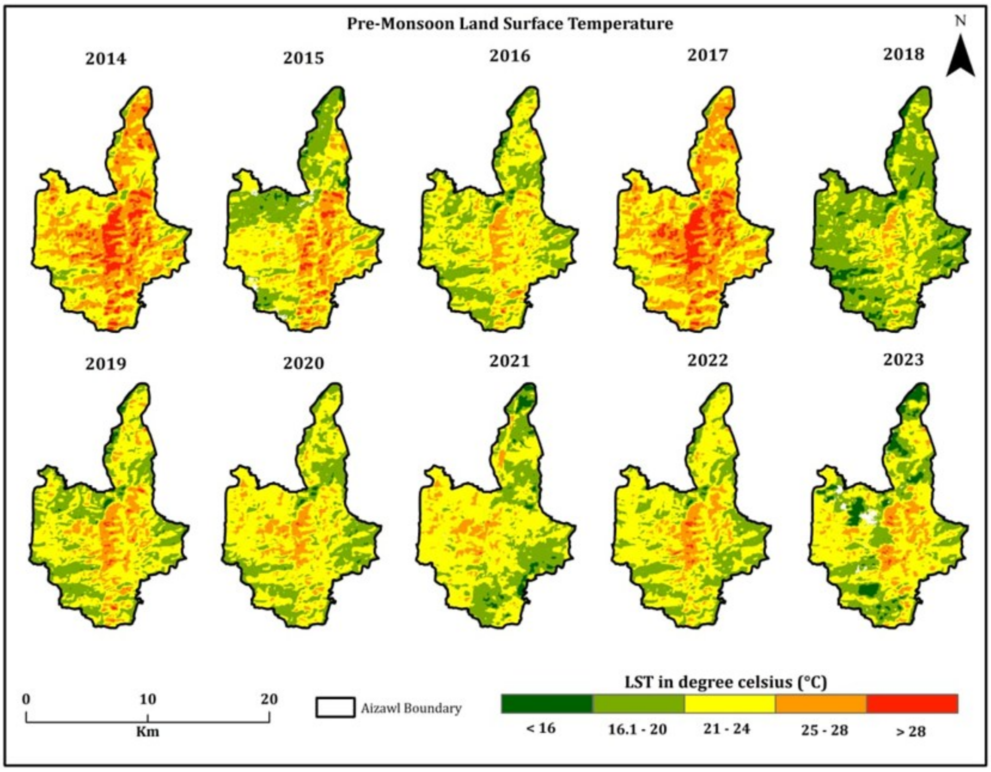


Fig. 3. *Map showing pre-monsoon Land surface temperature (LST) Aizawl in celsius degree*

encing mean temperature beyond simple linear trend, the minimum temperature had an R-squared value of 0.452, suggesting 45.2% of the variability. The model showed fluctuations with dips in years like 2017 and 2019 followed by a rise in 2020, indicating year-to-year variability in minimum LST (Fig. 4 and 5).

Post-monsoon Land surface temperature (LST) Aizawl

The linear regression analysis for the post-monsoon maximum temperature in Aizawl resulted in a slope of 0.016 with an intercept of 26.34 with a value of 0.048 and a P-value of 0.501, indicating that the trend was not statistically significant, mean temperature had linear regression slope of 0.010 showing a little increase in trends with the intercept of 20.23 and the R^2 value of 0.072 depicting that the linear model analyses only 7.2% of the variability, the P-value of 0.409 also showed that the trend was not statistically significant, the mean temperature had a slope value of 0.007 with an intercept of 14.22. The R^2 value was 0.062 and the P-value was 0.441, suggesting a slight LST increase.

The polynomial regression with a degree of 3 provided more detailed and intricate LST fluctuations. The R^2 value of 0.327 showed a better fit than linear regression, resulting in significant fluctuations and dips in certain years. For mean LST the polynomial regression had an R^2 value of 0.354. Minimum LST had an R^2 value of 0.296, suggesting that minimum LST also differs slightly from year to year. (Fig. 6,7).

Post-Monsoon Land surface temperature (LST) Agra

The maximum LST linear regression gave the slope value of 0.021, indicating a slightly increasing in LST trends; the intercept had a value of 30.42 “with an R^2

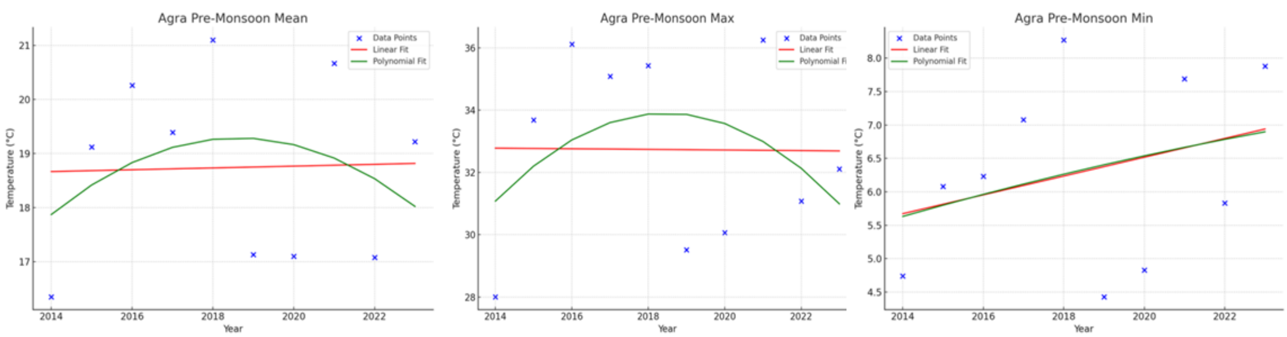


Fig. 4. *Agra Pre-Monsoon regression charts showing surface temperature (Max, Mean, Min)*

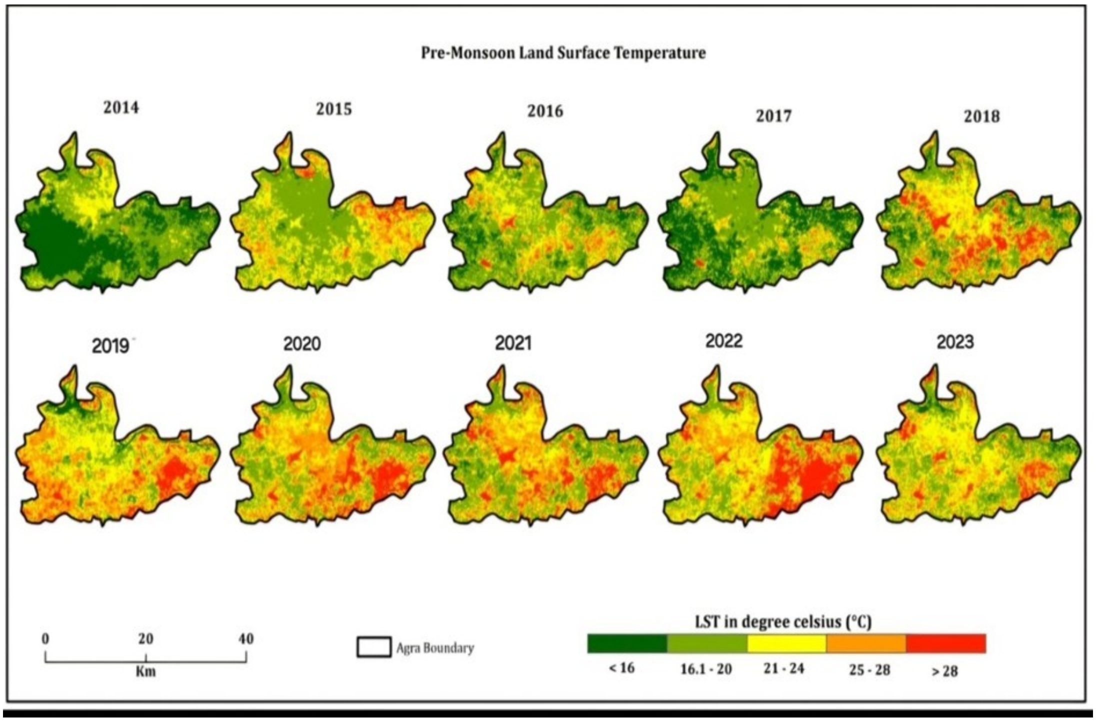


Fig.5. *Map showing pre-monsoon Land surface temperature (LST) Agra in celsius degree*

value of 0.112 and a P-value of 0.319, the mean temperature's linear slope was 0.018 with an intercept of 25.47and the R-squared value is 0.094 with the P-value of 0.359, suggesting that the trend was not statistically significant, but also suggested that it increases over the years. The minimum temperatures analysis gave a slope result of 0.014, with an intercept at 20.13, the R-squared value of 0.075, and the P-value of 0.403. The polynomial regression for maximum temperature gave R-squared results of 0.391, showing a good fit and suggesting fluctuations. Mean temperature had an R^2 value of 0.378, while minimum LST had an R^2 value of 0.343, indicating year-to-year variability.

Overall (Table 2), the analysis indicates that the long-term trend showed a slight increase in LST for both Agra and Aizawl cities; however, the year 2020 experienced decreasing in mean and minimum LST during both pre-monsoon and post-monsoon, this decrease in trends could be influenced by various factor, especially the climatic anomalies and reduced human activities during COVID-19 pandemic. The detailed year-to-year variability captured by polynomial regression focuses on the complexity of temperature trends and underscores the significance of advanced statistical models in climate studies (Fig. 8 and 9)

Relationship of Land surface temperature (LST) with spectral indices

In LST studies, it is clear that multiple factors influenced LST. Studying the relationship of LST with various remote sensing spectral indices is important for understanding the impact of urbanization on the environment. To understand this relationship, several remote sensing spectral indices were calculated, which are shown below:

NDBI (Normalized Difference Built-up Index): Calculating middle-infrared spectrum compared to the near-infrared in electromagnetic spectrum region was used to highlight and identify built-up areas. The higher values indicated the manmade objects or built-up area,

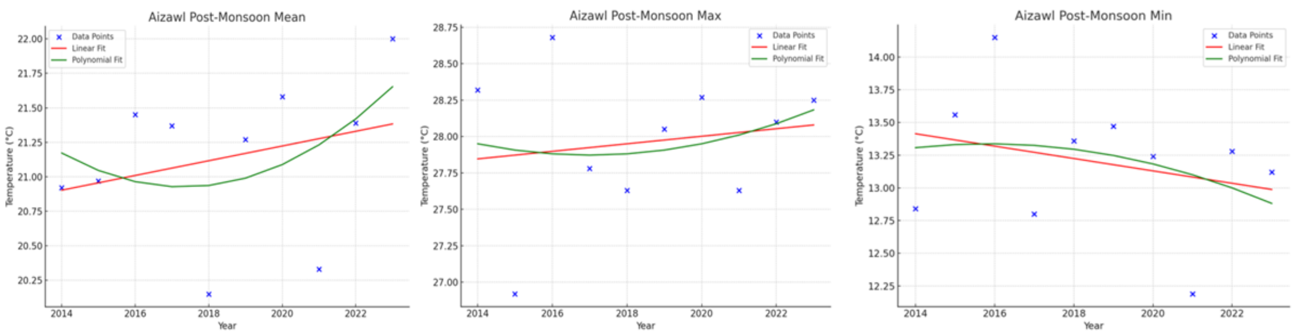


Fig. 6. *Aizawl Post-monsoon regression charts showing surface temperature (Max,Mean, Min)*

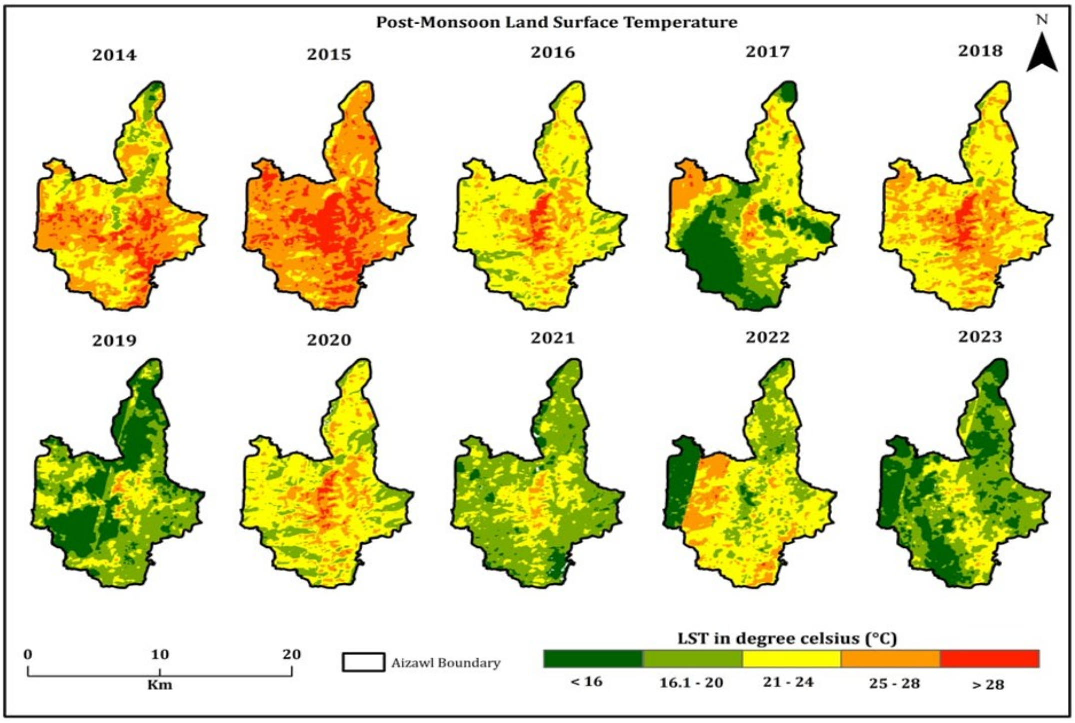


Fig. 7. *Maps showing post-monsoon Land surface temperature (LST) Aizawl in celsius degree*

which was useful for studying the urbanization

NDVI (Normalized Difference Vegetation Index): NDVI was calculated using the near-IR and red bands in the remote sensing satellite images. The NDVI was produced and used to highlight the vegetation. Higher NDVI values indicate the greenness of the region.

BSI (Bare Soil Index): BSI was calculated by comparing the visible and shortwave infrared bands. Highlighting the exposed soil region indicated that given higher values, there was less vegetation or other covered areas.

NDMI (Normalized Difference Moisture Index): NDMI was useful in highlighting the moisture content in vegetation using the near-infrared and shortwave infrared bands in the remote sensing satellite.

NDBaI (Normalized Difference Bareness Index): using the visible and shortwave infrared bands, NDBaI was calculated, which highlighted the bare soil and less vegetation area with the higher values the values ranged from -1 to +1

Fig. 15 and 16 show the above spectral indices, and their correlations with LST are explained below.

This analysis helped to understand the complex land cover types and their influence on urban thermal dynamics, which is also important for future environmental planning.

Normalized Difference Vegetation Index (NDVI)

LST and NDVI correlation are heavily influenced by spatial and temporal factors. The analysis shows a negative correlation between LST and NDVI with different strengths in Aizawl and Agra (Fig. 10). Aizawl had a correlation coefficient of -0.210. This explains that in Aizawl city, vegetation cover tends to have lower temperatures. Also, Agra City showed a negative correlation of -0.109. The result suggests that Agra had a lower effect of vegetation on LST than Aizawl, and the impact of vegetation or greenness on LST was more evident in Aizawl than in Agra.

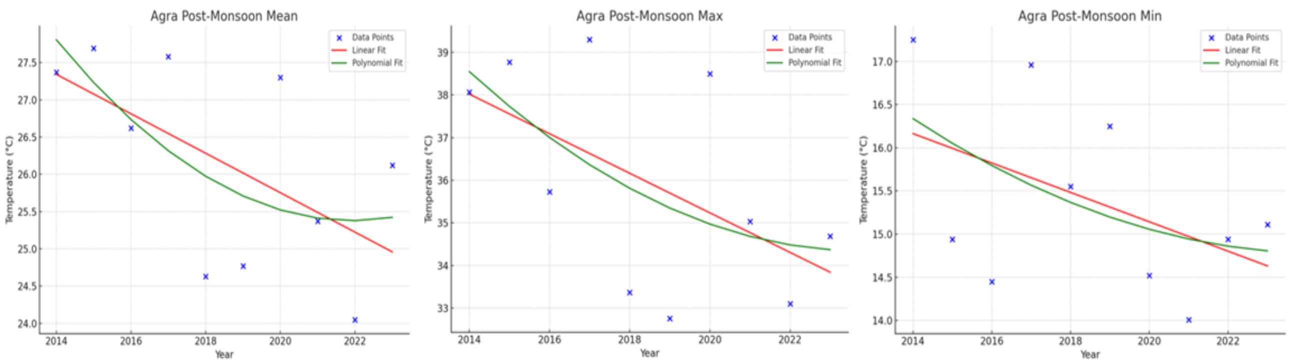


Fig. 8. *Agra Post-monsoon regression charts showing surface temperature (Max, Mean, Min)*

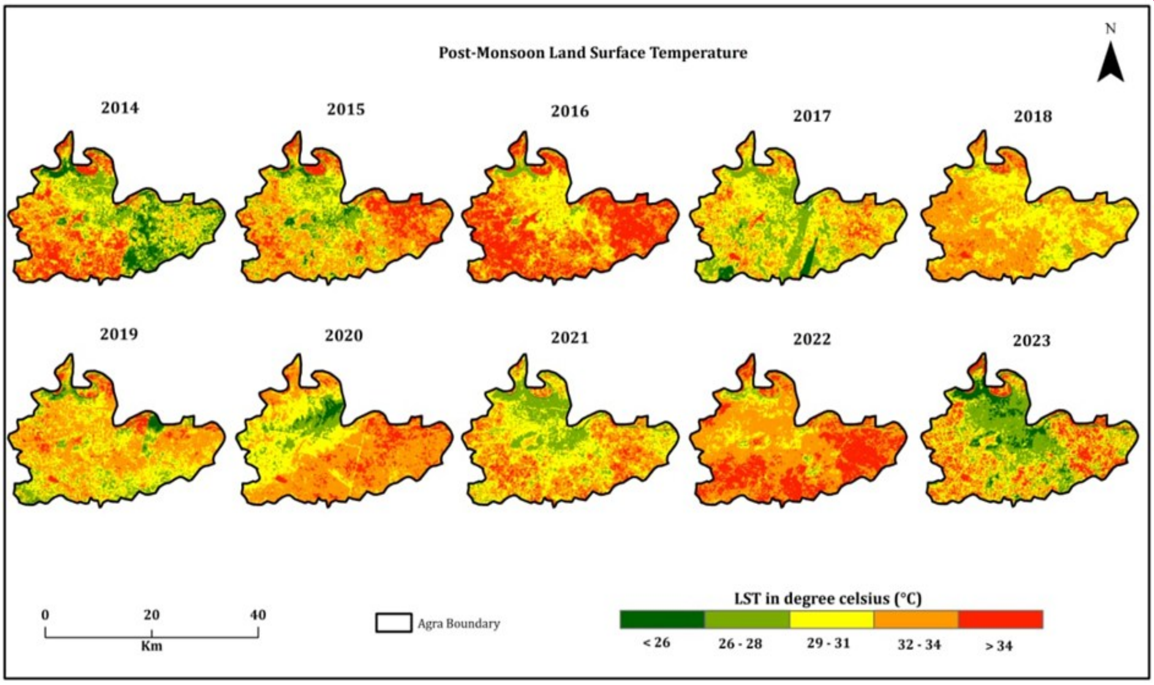


Fig.9. Map showing post-monsoon Land Surface Temperature of Agra

Normalized Difference Built-up Index RMA (NDBI)
The correlation analysis of NDBI and LST provides the built-up and manmade structures' influence on the LST, which suggested a positive correlation (Fig. 11). Agra had a correlation coefficient 0.343. This indicated that as built-up areas increased, LST had a corresponding rise. Aizawl had a stronger positive correlation than Agra, with a coefficient of 0.430. This result shows that the impact of built-up areas on LST was more evident in Aizawl than in Agra city

Normalized Difference Moisture Index (NDMI)
The correlation assessment of NDMI and LST revealed a significant negative correlation (Fig. 12). In Agra, the correlation coefficient is -0.343, indicating a moderate negative relationship. Aizawl also showed a negative correlation with a coefficient of -0.430, strongly indicating an even more pronounced relationship between moisture content and lower temperatures.

Normalized Difference Bareness Index (NDBaI)
NDBaI revealed a strong positive relationship with LST in both cities (Fig. 13). Aizawl's correlation coefficient is 0.519, a significant positive association between NDBaI and LST. Agra had a stronger correlation, with a coefficient of 0.78. These results showed the substantial impact that surface bareness and manmade objects had on the temperature of urban environments. The higher positive correlation showed that areas with barer surfaces or reduced vegetation cover tended to experience higher LST. The higher the bareness cover area, the greater the rise in LST.

Bare Soil Index (BSI)
The BSI is also an important tool for calculating surface bareness, unlike NDBaI was used specifically for identifying bare soil. In both cities, BSI showed a positive correlation with LST (Fig.14). In Agra, the correlation coefficient was 0.361 and Aizawl showed a higher cor-

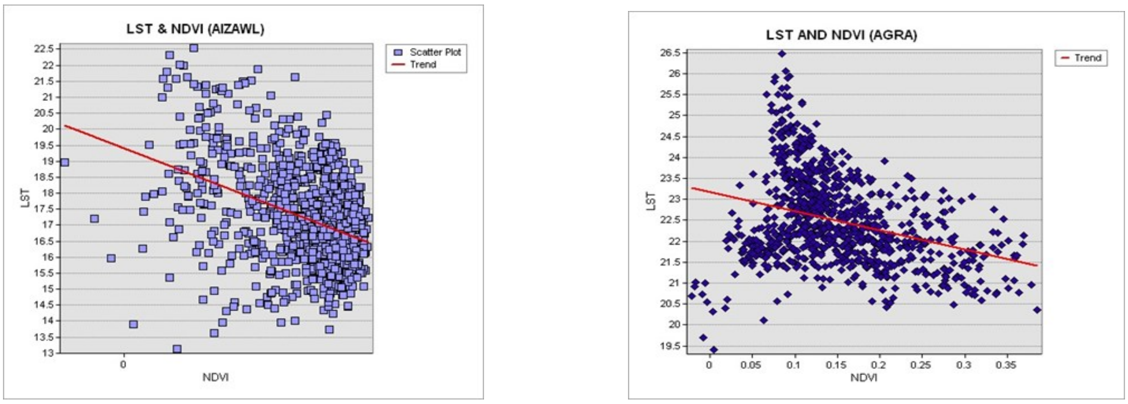


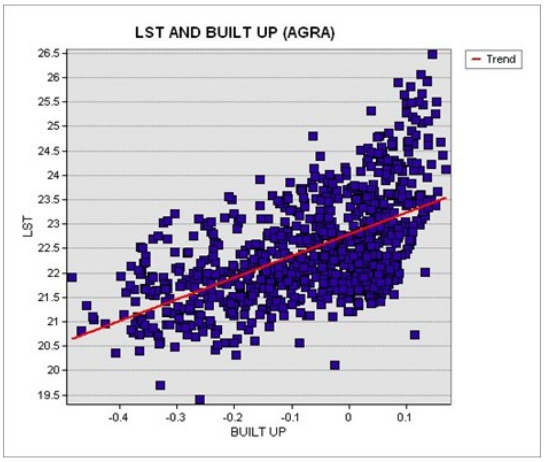
Fig.10. *Scatter plots showing LST and NDVI relationship*

Table 1. Pre-Monsoon Linear and Polynomial regression data

Study	Temperature	Linear				Polynomial	
		Slope	Intercept	R-squared	P-value	coefficients	R-squared
Aizawl	Minimum	-0.016	15.67	0.050	0.495	0.00, -0.009, 0.007, 0.001	0.3
	Mean	-0.02	22.15	0.085	0.319	0.00, -0.015, 0.013, 0.002	0.40
	Maximum	0.044	29.23	0.112	0.319	0.00, 0.011, -.009, 0.001	0.47
Agra	Minimum	0.026	25.56	0.221	0.153	0.00, 0.007, -0.006, 0.001	0.45
	Mean	0.032	31.28	0.188	0.194	0.00, 0.008, -0.007, 0.001	0.49
	Maximum	0.036	36.17	0.157	0.238	0.00,0.009, -008,0.002	0.52

Table 2. Post-monsoon Linear and Polynomial regression data of Aizawl and Agra

Study	Temperature	Linear				Polynomial	
		Slope	Intercept	R-squared	P-value	coefficients	R-squared
Aizawl	Minimum	0.007	14.22	0.062	0.441	0.00,-0.001, 0.001,0.0001	0.296
	Mean	0.010	20.23	0.072	0.409	0.00,-0.001, 0.001,0.0001	0.354
	Maximum	0.016	26.34	0.048	0.501	0.00,-0.002, 0.001,0.0002	0.327
Agra	Minimum	0.014	20.13	0.075	0.403	0.00,0.001, -0.001, 0.0002	0.343
	Mean	0.018	25.47	0.094	0.359	0.00, 0.002, -0.001, 0.0002	0.378
	Maximum	0.021	30.42	0.112	0.319	0.00,0.003, -.002,0.0003	0.391



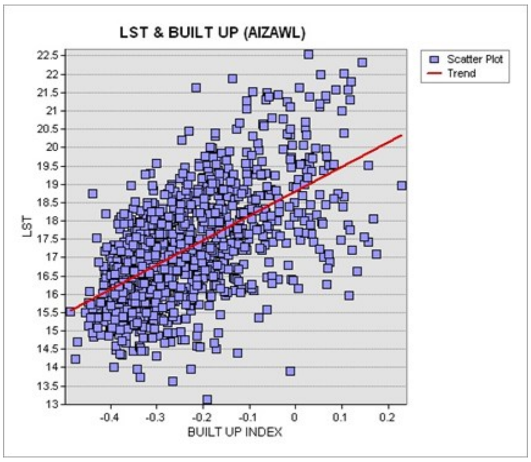


Fig. 11. *Scatter plots showing LST and NDBI relationship*

relation with a coefficient of 0.457. These correlations indicated that as the amount of bare soil increased, so did the surface temperature. This suggests that areas with more exposed soil contributed to higher temperatures, signifying the importance of vegetation cover in cooling the urban environment.

DISCUSSION

Urbanization has a significant impact on LST and UHI characteristics. Many previous studies investigated the impact of different land cover on LST in Delhi (Grover and Singh, 2015) and Kolkata (Guha *et al.*, 2018). While a number of the researchers focused on large metropolitan areas, the present study utilized geospatial techniques to analyse and compare LST trends in Agra and Aizawl cities (2014-2023). It also studied the effect of human-induced climate changes during the COVID-19 lockdowns, capturing how human activities modified the in-situ urban climate. The relationship between urbanization and LST had already been studied in Delhi, India (Grover and Singh, 2015) and Kolkata, India (Guha et al., 2018), but this study supported these claims with statistical modelling, long-term trend

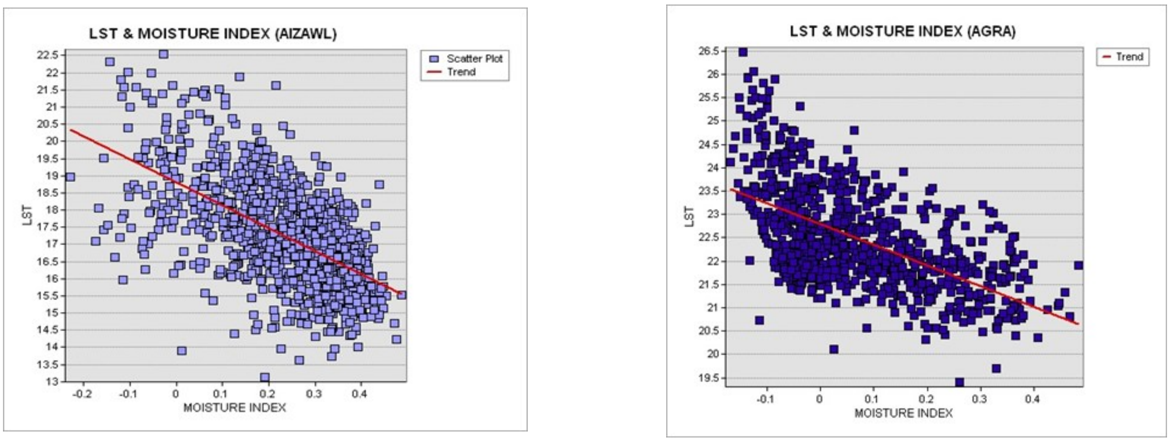


Fig. 12. *Scatter plots showing LST and NDMI relationship*

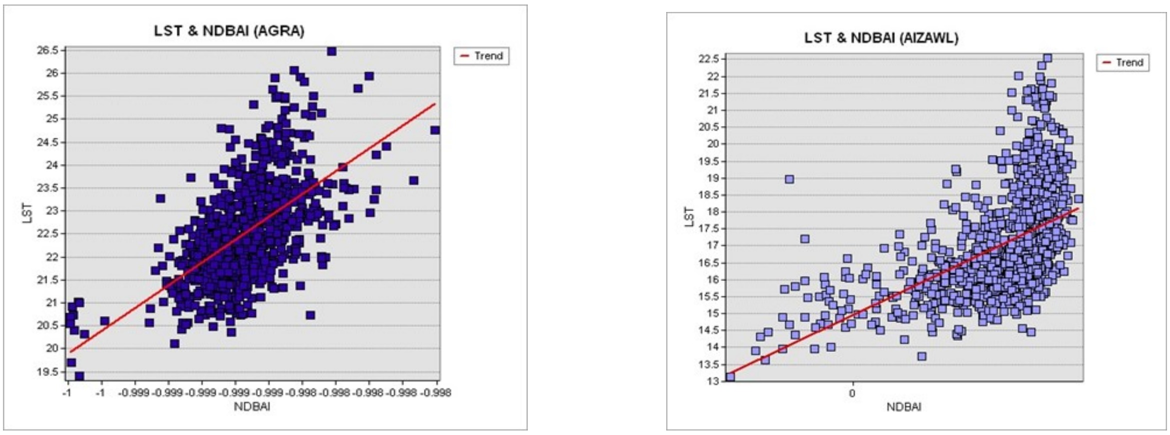


Fig. 13. *Scatter plots showing LST and NDBaI relationship*

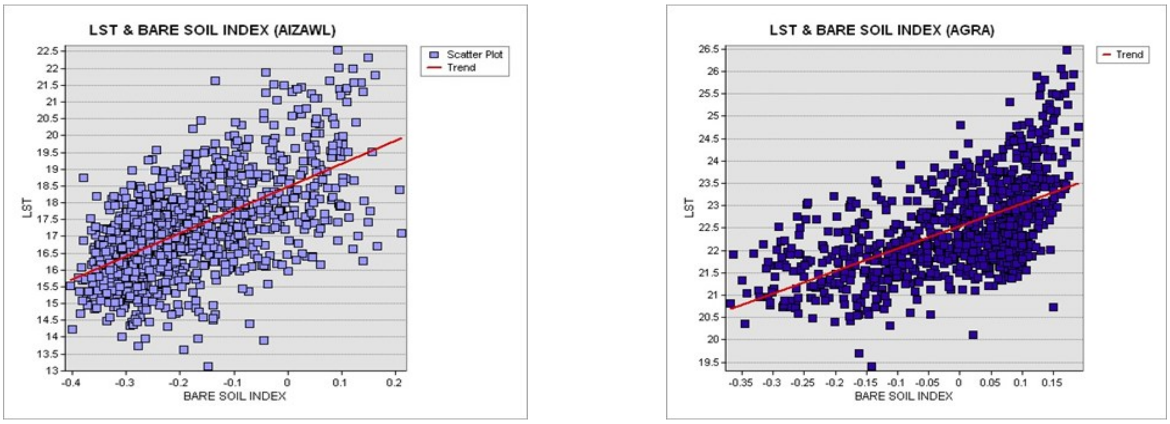


Fig. 14. *Scatter plots showing LST and BSI relationship*

analysis, and assessing the impact of the COVID lockdown on urban temperature. Additionally, this study highlights the significant capabilities of geospatial technology for studying urban thermal dynamics in compliance with the previous research (Li *et al.,* 2013; Qin *et al.,* 2001). However, the present study incorporates remote sensing techniques with several statistical methodologies, such as regression, correlation analysis, and time-series analysis, to better understand and accurately evaluate LST fluctuations in Urban environments. The analysis of pre-monsoon and post-monsoon LST trends (Tables 1 and 2, Fig. 2, 3, 4, 5, 6, 7,8 and 9) revealed that both cities experienced an overall increase in surface temperatures between 2014 and 2023. Agra demonstrated a consistently higher LST than Aizawl, attributed to its dense built-up infrastructure, limited green cover, and geographical setting. The polynomial regression results further highlight notable interannual fluctuations, emphasizing the influence of climate variability and land use changes (Fig. 8 and 9).

In Aizawl, the LST increase is relatively moderate, with considerable annual fluctuations. The polynomial regression model captured temperature dips in 2018 and 2020 (figure 2 and 6). Conversely, Agra exhibited a steadier increase in LST, particularly in the built-up are-

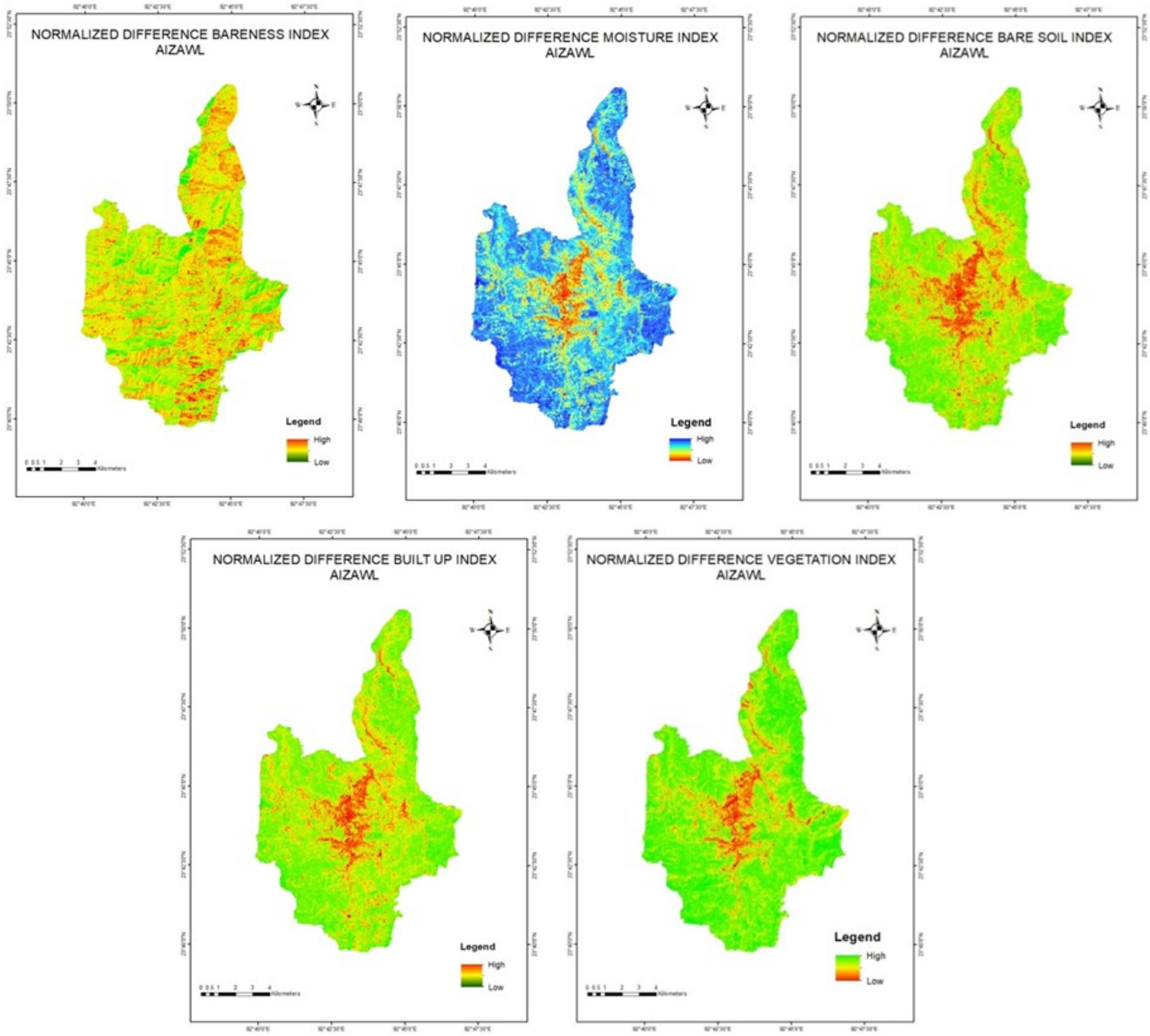


Fig.15. *Map showing different spectral indices of Aizawl*

as, reinforcing the established understanding of urban heat island (UHI) effects (Fig. 4,8 and 11).

The negative correlation between LST and vegetation index (NDVI) of our study is consistent with prior findings of Bechtel (2015) and Li *et al.* (2013).A negative correlation was observed between LST and NDVI in both cities, with Aizawl (-0.210) showing a stronger cooling effect of vegetation compared to Agra (-0.109).LST showed a strong positive correlation with built-up indices such as NDBI, BSI, and NDBaI. In Agra, the correlation coefficient between LST and NDBaI reached 0.78, indicating the substantial contribution of impervious surfaces to temperature rise. Aizawl, with a lower but still significant correlation (0.519), demonstrated a similar trend, albeit with a relatively higher vegetation cover buffering the impact. Also, the positive correlation between LST and built-up indices (NDBI, BSI, NDBaI) in the present study supports existing research (Guha *et al.,* 2018; Mathew *et al.,* 2017).

However, by using polynomial regression, the present study extends this understanding by depicting seasonal variations; this contrast with the traditional linear regression approaches, which show a steady rise in LST, the present study showed variation in annual LST patterns, which can depict the human impact on LST particularly during the COVID-19 lockdown. Also, the present findings explicitly compare two geographically and climatically distinct cities, showing that while both Agra and Aizawl exhibited similar correlation patterns, the degree of these relationships varied due to regional variation in urban density, greenspace and physiography. This variation necessitates city-specific urban planning strategies and a more nuanced view of urban temperature dynamics.

This study's key importance is its analysis of the effect of the 2020 COVID-19 lockdown on the urban climate, while previous efforts (Saha *et al.,* 2024; Vanlalchhuanga et al. 2022) noted a decrease in land surface temperature (LST) during the COVID-19 lockdown, one of the notable findings of this study is the observed decline in LST in 2020, particularly in mean and minimum temperatures (Tables 1 and 2). This trend aligns with the global reduction in anthropogenic activities during

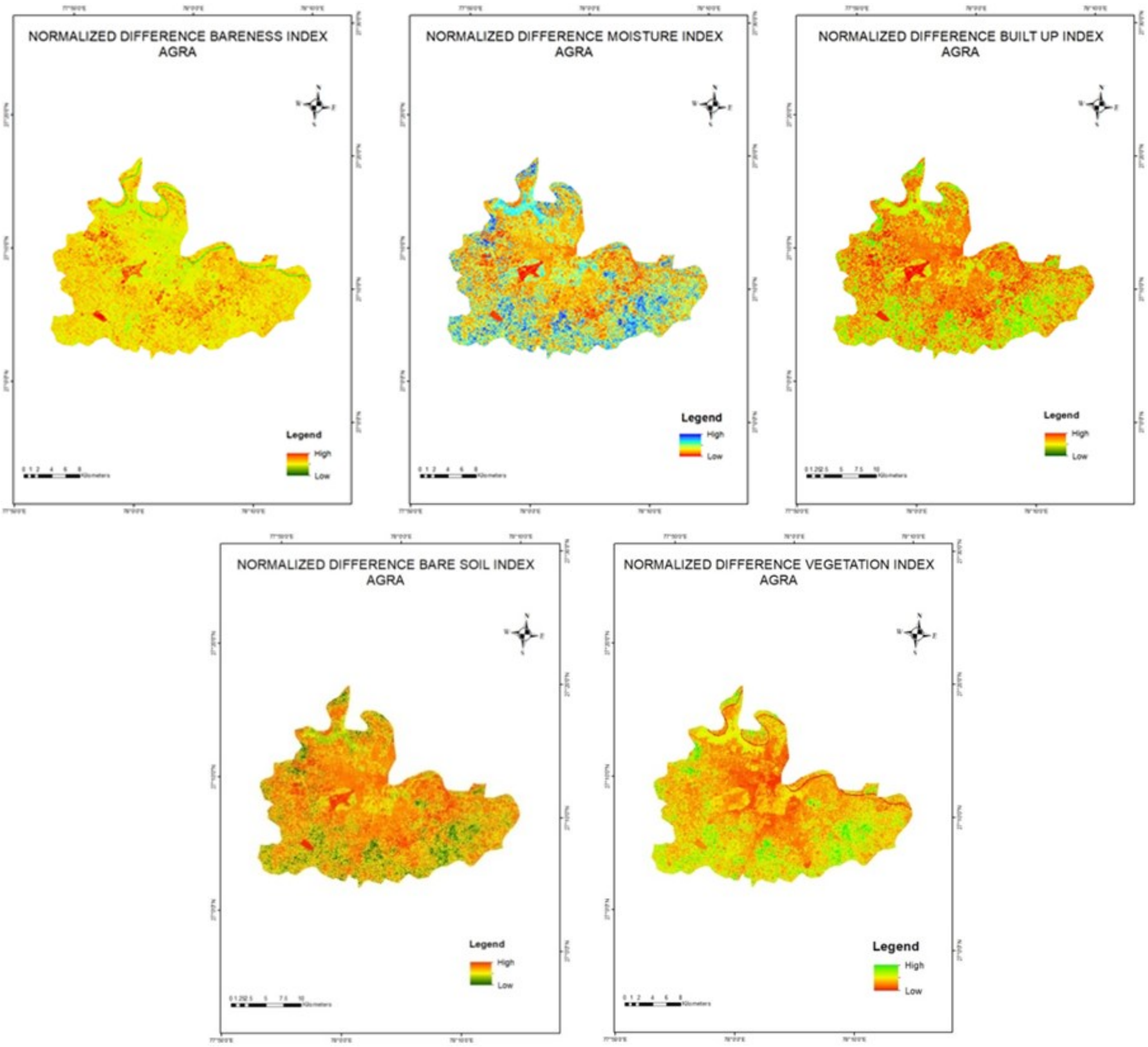


Fig.16. *Map showing different spectral indices of Agra*

the COVID-19 pandemic lockdown. The polynomial regression results (Fig. 18, 19, 20, and 21) capture this anomaly, emphasizing the temporary but measurable cooling effect of reduced industrial, vehicular, and commercial activities. The present study assesses change in LST, mean and minimum, across two urban regions in India, and finds that short-term abatement of anthropogenic activities can mitigate urban warming. The present study highlights the relevant LST differential aspects in Agra and Aizawl, while statistical tables and Fig. describe the highlighted relationships meaningfully. The diversity of LST trends between cities affirms that the configuration of urban areas and landscapes shapes surface temperature distribution. This knowledge can be helpful in sustainable urban planning by signifying a scrolling of the need to preserve/create green space.

This study correlates with the established literature, but its innovation is derivable from (i) the comparative review of two contrasting urban environments, (ii) the utilization of polynomial regression to analyse trends, (iii) the quantification of the COVID-19 lockdown effect upon LST (iv) the combination of different analytical techniques. These insights deepen knowledge of how cities manage their heat, offering practical pathways for urban governance.

Conclusion

This study analyzed LST trends in Agra and Aizawl from 2014 to 2023, assessing their relationship with remote sensing spectral indices to understand urbanization's impact on UHI. The findings highlight a consistent increase in LST, with Agra showing a more substantial urban heat effect due to higher built-up density, while Aizawl's terrain and vegetation mitigate temperature rise. The correlation analysis underscores the role of vegetation in cooling urban areas (negative NDVI-LST correlation) and the contribution of built-up surfaces to temperature increases (positive NDBI-LST correlation). The study also highlights the temporary LST decline in 2020 due to reduced anthropogenic activities during the COVID-19 lockdown, demonstrating the direct influence of human activities on urban climate.

Urban policies should prioritize green infrastructure, sustainable construction, and climate-resilient planning to mitigate rising temperatures. The findings provide valuable insights for policymakers in developing sustainable urban strategies that balance growth with environmental considerations. Future research should refine localized urban heat assessments, integrating high -resolution data to develop more targeted mitigation strategies for climate-resilient cities.

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Conflict of interest

The authors declare that they have no conflict of interest.

REFERENCES

1. Aires, F., Prigent, C., Rossow, W. B., & Rothstein, M. (2001). A new neural network approach including first guess for retrieval of atmospheric water vapor, cloud liquid water path, surface temperature, and emissivities over land from satellite microwave observations. *Journal of Geophysical Research: Atmospheres*, *106*(D14), 14887-14907.
2. Bechtel, B. (2015). A new global climatology of annual land surface temperature. *Remote Sensing*, *7*(3), 2850-2870. https://doi.org/10.3390/rs70302850
3. Chakraborty, S. D., Kant, Y., & Bharath, B. D. (2014). Study of land surface temperature in delhi city to managing the thermal effect on urban developments. *International journal of advanced scientific and technical research*, *4*(1), 439- 450.
4. Dickinson, R. E. (1995). Satellite systems and models for future climate change. In *World Survey of Climatology* (Vol. 16, pp. 245-279). Elsevier.
5. Frey, C. M., & Kuenzer, C. (2014). Land-surface temperature dynamics in the Upper Mekong Basin derived from MODIS time series, *International Journal of Remote Sensing*,35:8,2780-2798,https://doi.org/10.1080/0143 1161.2014.890304
6. Grover, A., & Singh, R. B. (2015). Analysis of urban heat island (UHI) in relation to normalized difference vegetation index (NDVI): A comparative study of Delhi and Mumbai. *Environments*, *2*(2), 125-138. https://doi.org/10.3390/ environments 2020125.
7. Guha, S., Govil, H., Dey, A., & Gill, N. (2018). Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy. *European Journal of Remote Sensing*, *51*(1), 667-678. https://doi.org/10.1080/22797254.20 18.1474494.
8. Hussain, S., Raza, A., Abdo, H. G., Mubeen, M., Tariq, A., Nasim, W., ... & Al Dughairi, A. A. (2023). Relation of land surface temperature with different vegetation indices using multi-temporal remote sensing data in Sahiwal region, Pakistan. *Geoscience Letters*, *10*(1), 33. https://doi.org/10.1186/s40562-023-00287-6
9. Jin, M., & Liang, S. (2006). An improved land surface emissivity parameter for land surface models using global remote sensing observations. *Journal of Climate*, *19*(12), 2867-2881.
10. John, J., Bindu, G., Srimuruganandam, B., Wadhwa, A., & Rajan, P. (2020) Land use/land cover and land surface temperature analysis in Wayanad district, India, using satellite imagery, *Annals of GIS*. https://doi.org/10.10 80/19475683. 2020.1733662.
11. Johnston, R. J. (2006). Geography and GIS. In PA. Longley, MF. Goodchild, DJ. Maguire, & DW. Rhind (Eds.), Geographical Information Systems: Principles, Techniques, Management and Applications (2nd edition, abridged) (pp. 27 - 35). John Wiley & Sons, Ltd.
12. Kikon, N., Kumar, D., & Ahmed, S. A. (2023). Quantitative assessment of land surface temperature and vegetation indices on a kilometer grid scale. *Environmental Science and Pollution Research*, *30*(49), 107236-107258.https://doi.org/10.1007/s11356-023-27418-y
13. Li, Z. L., Tang, B. H., Wu, H., Ren, H., Yan, G., Wan, Z., ... & Sobrino, J. A. (2013). Satellite-derived land surface temperature: Current status and perspectives. *Remote sensing of environment*, *131*, 14-37. https://doi:10.1016/j.rse. 2012.12.008.
14. Li, X., Zhou, W., & Ouyang, Z. (2013). Relationship between land surface temperature and spatial pattern of greenspace: What are the effects of spatial resolution?, *Landscape and Urban Planning*, 114,1– 8.
15. Mallick, J., Kant, Y., & Bharath, B. D. (2008). Estimation of land surface temperature over Delhi using Landsat-7 ETM+. *Journal of Indian Geophysical Union*, *12*(3), 131-140.
16. Masek, J. G., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., ... & Lim, T. K. (2006). A Landsat surface reflectance dataset for North America, 1990-2000. *IEEE Geoscience and Remote sensing letters*, *3*(1), 68-72.
17. Mathew, A., Khandelwal, S., & Kaul, N. (2017). Investigating spatial and seasonal variations of urban heat island effect over Jaipur city and its relationship with vegetation, urbanization and elevation parameters. *Sustainable cities and society*, *35*, 157-177. http://dx.doi.org/doi:10.1016/j.scs.2017.07.013
18. Mustafa, E. K., Co, Y., Liu, G., Kaloop, M. R., Beshr, A. A., Zarzoura, F., & Sadek, M. (2020). Study for predicting land surface temperature (LST) using landsat data: a comparison of four algorithms. *Advances in Civil Engineering*, *2020*(1), 7363546.https://doi.org/10.115 5/2020/7363546.
19. Qin, Z., Karnieli, A., & Berliner, P. (2001). A mono-window algorithm for retrieving land surface temperature from Landsat TM data and its application to the Israel-Egypt border region. *International journal of remote sensing*, *22*(18), 3719-3746. https://doi.org/10.1080/01 431160010006971
20. Ramachandra, T. V., Aithal, B. H., & Sanna, D. (2012).

Land surface temperature analysis in an urbanising landscape through multi-resolution data. *Research & Reviews: Journal of Space Science & Technology*, *1*(1), 1-10.

21. Saha, J., Ria, S. S., Sultana, J., Shima, U. A., Seyam, M. M. H., & Rahman, M. M. (2024). Assessing seasonal dynamics of land surface temperature (LST) and land use land cover (LULC) in Bhairab, Kishoreganj, Bangladesh: A geospatial analysis from 2008 to 2023. *Case Studies in Chemical and Environmental Engineering*, *9*, 100560. https://doi.org/10.1016/j.cscee.2023.100560
22. Sajan, B., Kanga, S., Singh, S. K., Mishra, V. N., & Durin, B. (2023). Spatial variations of LST and NDVI in Muzaffarpur district, Bihar using Google earth engine (GEE) during 1990-2020. *Journal of agrometeorology*, *25* (2), 262-267. https://doi.org/10.54386/jam.v25i2.2155
23. Sentinel-5," ESA, URL: https://sentinel.esa.int/web/sentinel/missions/sentinel-5
24. Talukdar, K. K., & Arsac, A. C. (2020). Land surface temperature retrieval of Guwahati city and suburbs, Assam, India using Landsat Data. *International Journal of Engineering Research Technology*, *9*, 882-887.
25. Uttara, S., Bhuvandas, N. and Aggarwal, V., (2012). Impacts of urbanization on environment. *International Journal of Research in Engineering and Applied Sciences*, 2(2), 1637-1645
26. Vanlalchhuanga, Biswas, B., & Barman, J. (2022). A Literature Review of the Impact of COVID-19 Pandemic on Land Surface Temperature and Air Quality of India. *Monitoring and Managing Multi-hazards: A Multidisciplinary Approach*, 117-123. https://doi.org/10.1007/978-3-031-15377-8_8
27. Vermote, E., Justice, C., Claverie, M., & Franch, B. (2016). Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. *Remote sensing of environment*, *185*, 46-56.