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Analyzing the Interrelationship between Land Surface Temperature, Environmental Indices, and Land Cover in Savar, Bangladesh

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Abstract: *This study explores how Land Surface Temperature (LST) is related to different land cover types, highlighting how vegetation and water bodies help reduce urban heat in Savar, Bangladesh. Using satellite imagery from the United States Geological Survey (USGS), LST and environmental indices— Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-Up Index (NDBI), Normalized Difference Moisture Index (NDMI), Soil-Adjusted Vegetation Index (SAVI), and Modified Normalized Difference Water Index (MNDWI) were employed to analyze the spatial distribution of LST and land cover types. The outcome reveals that densely built-up and industrial areas exhibit the highest LST due to impervious surfaces, while vegetated zones and water bodies, characterized by high NDVI, NDWI, and MNDWI values, show significantly lower LST. Areas with high NDMI and SAVI values also demonstrate effective temperature regulation by vegetation and soil moisture. Conversely, regions with high NDBI values correspond to higher LST, indicating the heat-retaining nature of urbanized areas. These findings underscore the importance of green and blue infrastructure in reducing urban heat and enhancing climate resilience. This study provides valuable insights for urban planners and policymakers, recommending the strategic expansion of green spaces, conservation of water bodies, and sustainable urban design to mitigate the impacts of urban heat in rapidly developing areas like Savar.*

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Keywords: Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI), Normalized Difference Built-Up Index (NDBI), Geospatial Analysis.

Introduction

The rapid pace of land use changes influence resources, environmental quality, community structures, and overall well-being of human lives and environmental systems (Gao & Liu, 2021; Seto et al., 2012). Research highlights that land use changes often result in habitat loss, biodiversity decline, and alterations in climate regulation, underscoring the need for sustainable management practices (Weiskopf et al., 2020).

Savar, a region near Dhaka, Bangladesh, has undergone significant urban expansion and industrial growth driven by residential, commercial, and industrial developments, particularly in garment manufacturing, leather processing, and other manufacturing sectors, fueling economic growth and creating employment opportunities due to its strategic location (Rahman & Alam, 2021). However, this rapid industrialization has led to severe environmental challenges, including rising land surface temperatures (LST), water pollution and degradation of local water bodies such as the *Dhaleshwari River*, air contamination, loss of vegetation and increased impervious surfaces, amplifying the urban heat island (UHI) effect (Ahmed et al., 2020). Monitoring LST is critical for assessing environmental impacts, as elevated temperatures contribute to health risks such as heat-related illnesses and mortality, emphasizing the need for effective temperature control strategies (Environmental Research Letters, 2021). Land surface temperature closely relates to land cover types, such as vegetation and water bodies. Spectral indices like the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) provide valuable insights into vegetation density and water content, respectively, and their influence on temperature dynamics (Remote Sensing of Environment, 2020). Studies on urban heat islands show that remote sensing indices, including NDVI, NDBI (Normalized Difference Built-Up Index), SAVI (Soil-Adjusted Vegetation Index), and NDWI, are effective for analyzing UHI effects. High NDBI values correlate with elevated LST due to urban density, while high NDVI values indicate lower temperatures, highlighting vegetation's cooling effect (Seto et al., 2012). For instance, research on LST in Rajshahi, Bangladesh, demonstrates how rising temperatures, particularly in winter, negatively affect agricultural yields, emphasizing the broader implications of temperature changes on both urban and rural environments (Faisal et al., 2021).

This study hypothesizes an inverse relationship between LST and indices related to vegetation and water, such as NDVI and NDWI. Dense vegetation and abundant water (high NDVI and NDWI values) correlate with lower LST, while areas with sparse vegetation and water content exhibit higher temperatures. Remote sensing techniques are more efficient than field surveys for monitoring LST and spectral indices across large areas, making them ideal for rapidly urbanizing regions like Savar. This research aims to quantify LST variations across land cover types, analyze the cooling effects of green and blue infrastructure, and establish relationships between LST and land cover indices. Insights from this study can inform policies for sustainable urban planning and UHI mitigation.

Study Area

The area of interest of this research is limited to Savar, situated on the outskirts of Dhaka, Bangladesh, span approximately 280.13 square kilometers (108.15 square miles), one of the largest upazilas in the Dhaka District. It is located within 23° 51' 30" N Latitude and 90° 16' 0" E Longitude. This area is strategically located northwest of Dhaka city and is bounded by the Dhaleshwari River, encompassing residential, industrial, and agricultural zones as well as natural wetlands. Savar is a growing industrial and residential hub close to the capital.

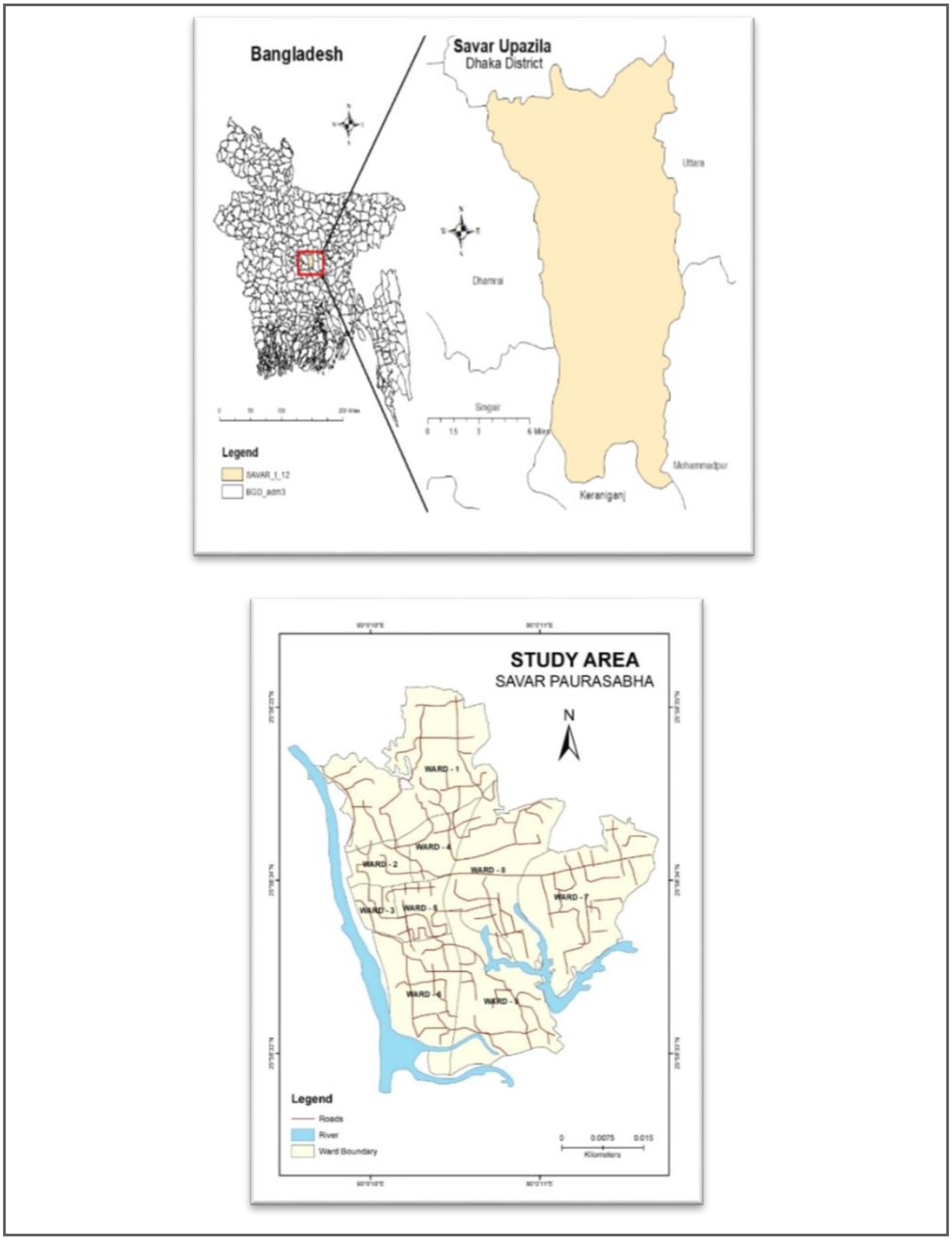


Figure 1: Study Area (Source:Authors,2024)

Methods

The methodology involves acquiring and preprocessing satellite imagery (Landsat), calculating LST, NDVI, and NDWI, and analyzing spatial-temporal patterns. Techniques include hotspot analysis, spatial autocorrelation, and regression modeling to explore land use impacts. Findings guide sustainable urban planning, emphasizing vegetation, water conservation, and temperature regulation for Savar's environmental resilience.

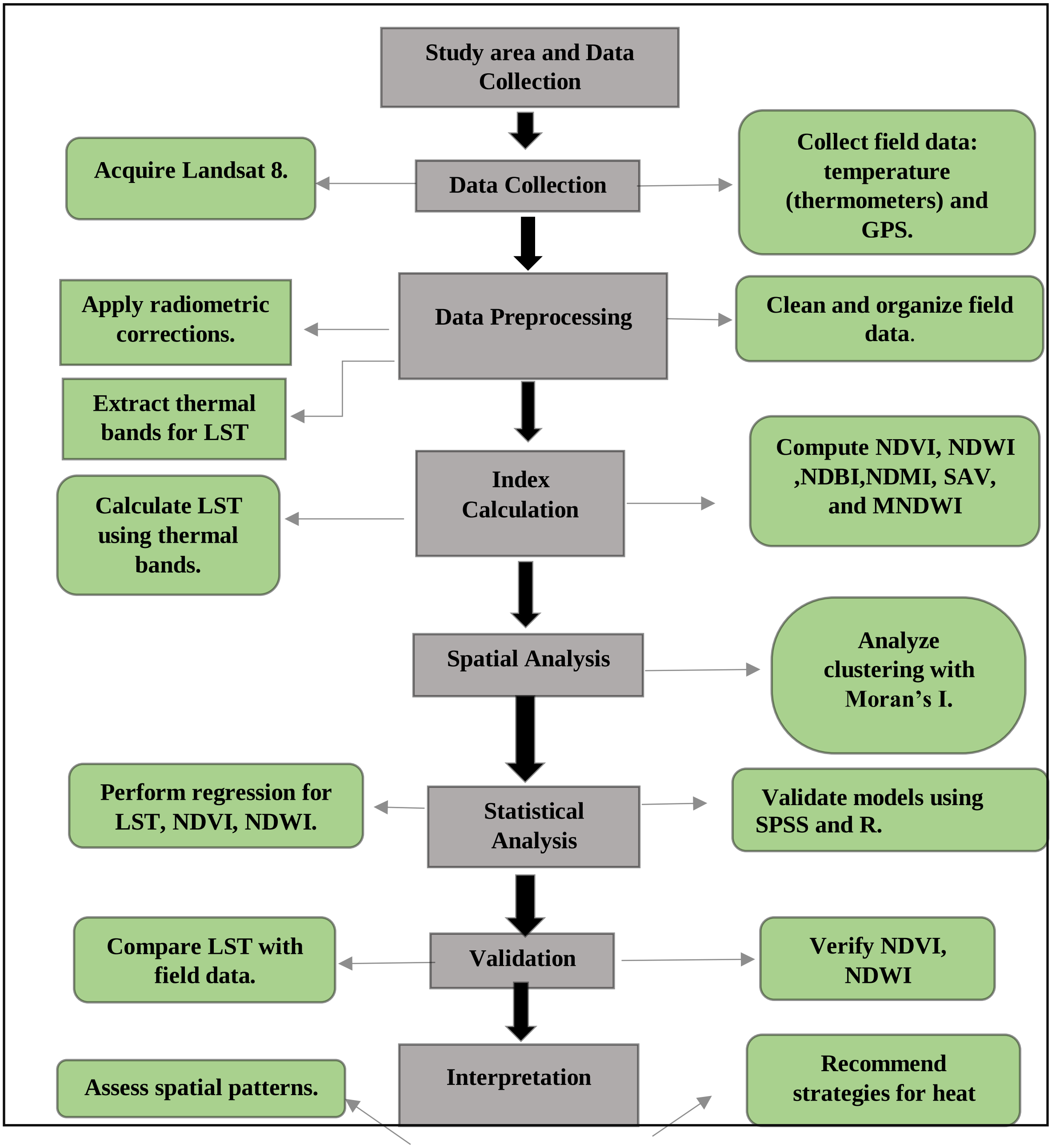


Figure 2: The methodological framework (Source- Authors,2024)

The study focuses on analyzing Land Surface Temperature (LST), vegetation index (NDVI), water index (NDWI), and Land Use/Land Cover (LULC) to understand their interrelations and impacts. The required data includes LST values, their temporal and spatial patterns, and validation data collected from field measurements. This data is sourced from satellite imagery such as Landsat (8 and 9), field surveys using thermometers, and auxiliary climate reports from government agencies.

Index Calculation

LST represents the temperature emitted from the Earth's surface and is derived using the thermal infrared (TIR) bands from Landsat 8/9. The steps for LST calculation are:

Table 1: Process of LST calculation

Steps	Associated Equations
Convert Digital Numbers (DN) to Top of Atmosphere (TOA) Radiance	$L_\lambda = ML \times Q_{cal} + AL$ Where: • L_λ: TOA radiance (W/m²/sr/µm) • ML: Radiance multiplier (provided in metadata) • AL: Radiance additive term (provided in metadata) • Q_{cal}: Quantized calibrated pixel value (DN)
Convert TOA Radiance to Brightness Temperature (BT)	$T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}$ Where: • T: Brightness temperature (Kelvin) • K_1, K_2: Calibration constants (provided in metadata) • L_λ: TOA radiance
Correct for Emissivity	$LST = \frac{T}{1 + (\lambda \times T/\rho)\ln \varepsilon}$ Where: • λ: Wavelength of emitted radiance • ρ: Planck's constant
Normalized Difference Vegetation Index (NDVI) that quantifies vegetation health by measuring the difference between near-infrared (NIR) and red reflectance.	$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$ Where: • NIR: Reflectance in near-infrared band • RED: Reflectance in red band
Normalized Difference Water Index (NDWI) assesses water content in vegetation and open water bodies.	$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$ Where: • $SWIR$: Reflectance in shortwave-infrared band

Normalized Difference Built-Up Index (NDBI) highlights built-up areas and urban development.	$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)}$
Normalized Difference Moisture Index (NDMI) evaluates moisture content in vegetation.	$NDMI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$
Soil-Adjusted Vegetation Index (SAVI) accounts for soil brightness, improving vegetation monitoring in sparse vegetative areas.	$SAVI = \frac{(NIR - RED)(1 + L)}{(NIR + RED + L)}$ Where: • L: Soil adjustment factor (typically 0.5)
Modified Normalized Difference Water Index (MNDWI) enhances water body detection by using green and SWIR bands.	$MNDWI = \frac{(GREEN - SWIR)}{(GREEN + SWIR)}$ Where: • $GREEN$. Reflectance in the green band
Moran's I Spatial Analysis	**Moran's I Formula:** $I = \frac{n}{W} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$ Where: • n = number of spatial units (e.g., districts or pixels) • x_i = variable value at location i • $\bar{x}$ = mean of the variable • w_{ij} = spatial weight between location i and j • $W = \sum_i \sum_j w_{ij}$ = total of all spatial weights
Regression Analysis	Before performing regression analysis, we examined the relationships between LST and the environmental indices through Pearson's correlation. This step helps identify the degree of association between LST and each of the indices. For example, the analysis showed: A significant positive correlation between LST and NDVI and NDBI, suggesting that areas with more vegetation (NDVI) and built-up structures (NDBI) tend to have higher LST. A negative correlation was observed between LST and NDWI, NDMI, and MNDWI, indicating that areas with more water or moisture tend to have cooler temperatures, highlighting the cooling effect of water bodies.

These indices provide a comprehensive framework for analyzing the spatial distribution of LST and environmental characteristics. NDVI and SAVI focus on vegetation health, NDWI and MNDWI assess water availability, NDBI highlights urban development, and NDMI evaluates moisture. Combined, these indices enable robust environmental and urban heat management strategies.

Result and Discussions:

LST Distribution

The Land Surface Temperature (LST) Map(figure 3) of Savar provides a comprehensive spatial overview of temperature variations across different wards in Savar *Paurashava* and surrounding unions, highlighting areas with distinct temperature ranges. The map divides temperatures into specific ranges (e.g., <26°C, 29-30°C, 30-31°C, 31-32°C, and >34°C), represented by different color gradients, allowing for the easy identification of hotspots and cooler zones within Savar.

Land Surface Temperature Map, Savar (2024)

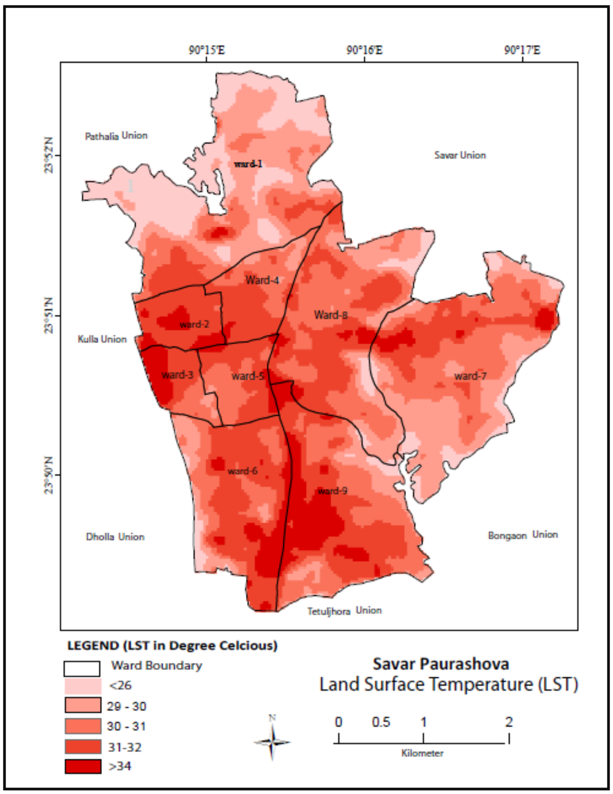


Figure 3: Land Surface Temperature of Savar (2024) (Source: Authors,2024)

The highest LST values, particularly those above 34°C, are concentrated in densely populated and industrialized sections, specifically in Ward-1 and Ward-4. These areas are characterized by substantial industrial activities, including factories and manufacturing plants, and are densely packed with urban infrastructure. The presence of impervious surfaces, such as roads, concrete structures, and industrial facilities, contributes to higher heat retention, intensifying the urban heat island effect. Geographically, these high-temperature wards are positioned close to the central industrial belt of Savar, an area that has seen rapid urban expansion, limited green space, and significant changes in land use.

In contrast, the wards with the lowest LST values, typically below 26°C, are generally found in areas with natural land cover, including vegetation and water bodies. Ward-7 and Ward-9 exemplify these cooler zones, likely featuring green spaces, agricultural fields, or proximity to water bodies, which help regulate temperature through shading, evapotranspiration, and increased surface albedo. These wards are located on the outskirts of the urban core, closer to rural or semi-urban landscapes where vegetation is more abundant, creating a cooling effect. This contrast between high and low LST areas underscores the influence of land use on temperature distribution, where urbanized and industrial zones experience more intense heat compared to greener, more natural areas.From a geographical perspective, the LST distribution in Savar reflects the different land use patterns and natural landscape features. The urban core, with wards like Ward-1 and Ward-4, acts as a heat island due to concentrated human activities and minimal vegetation. In contrast, peripheral wards, such as Ward-7 and Ward-9, benefit from their proximity to rural areas and water sources, which help mitigate heat buildup. The map also displays the boundaries of neighboring unions, such as Pathalia, Bongaon, Tetuljhora, Dholla, and Kulla, providing context for the spatial extent of the temperature analysis within Savar and its periphery.

Environmental Indices:

NDVI

The map shows the Normalized Difference Vegetation Index (NDVI) distribution across different wards in Savar Paurashava (municipality), which is a part of the Savar region. NDVI is a widely used index to measure vegetation health and density, with higher values indicating more vegetation coverage or healthier plants.

The map uses a gradient color scheme to display NDVI values, with six color classes ranging from light green to dark green. Lighter Greens represent lower NDVI values, suggesting areas with sparse vegetation, bare soil, built-up areas, or surfaces with little to no vegetation whereas Darker Greens indicate higher NDVI values, signifying dense or healthy vegetation, such as forested areas, parks, or agricultural fields. NDVI values on this map ranges from 0.023 to 0.45. Lower NDVI values (e.g., 0.023) are shown in very light green and are more likely to represent urban or built-up areas or places with limited vegetation. Higher NDVI values (e.g., 0.45) in darker green areas likely represent zones with a higher density of vegetation, such as parks, farmlands, or riverbanks with natural growth.

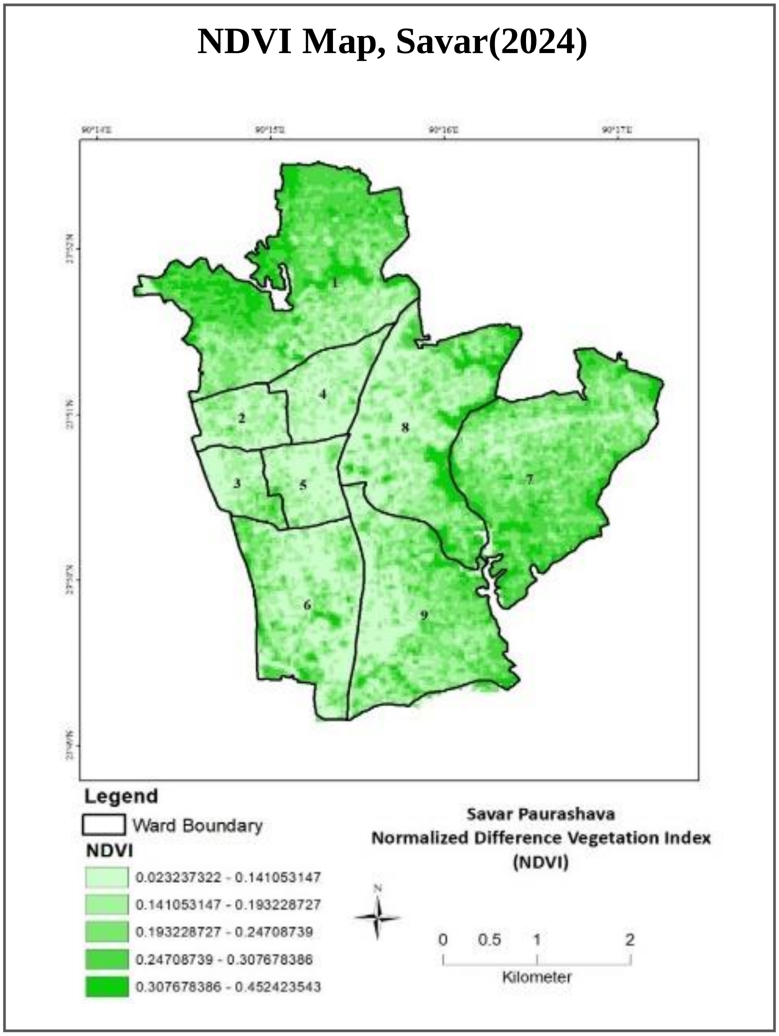


Figure 4: NDVI Map (Source- Authors,2024)

In figure 4, Wards with darker green areas have higher NDVI values, indicating more vegetation. These might include open green spaces or less urbanized zones within Savar. Lighter green regions likely correspond to more urbanized or developed areas where vegetation is sparse or less healthy. Urban structures tend to reduce the NDVI values due to the absence of photosynthetically active surfaces. The variation in NDVI values across Savar reflects differences in land use and vegetation density. Higher NDVI values in specific wards could contribute to local cooling effects, while lower NDVI values in built-up areas might relate to higher Land Surface Temperatures (LST) due to urban heat.

NDWI

The map visualizes the distribution of water bodies in Savar *Paurashava* through the Normalized Difference Waterbody Index (NDWI)**,** a remote sensing index used to highlight water features based on satellite imagery. NDWI is a valuable tool for identifying water bodies by analyzing the difference in reflectance between the near-infrared and green bands of light, with higher values indicating more water.

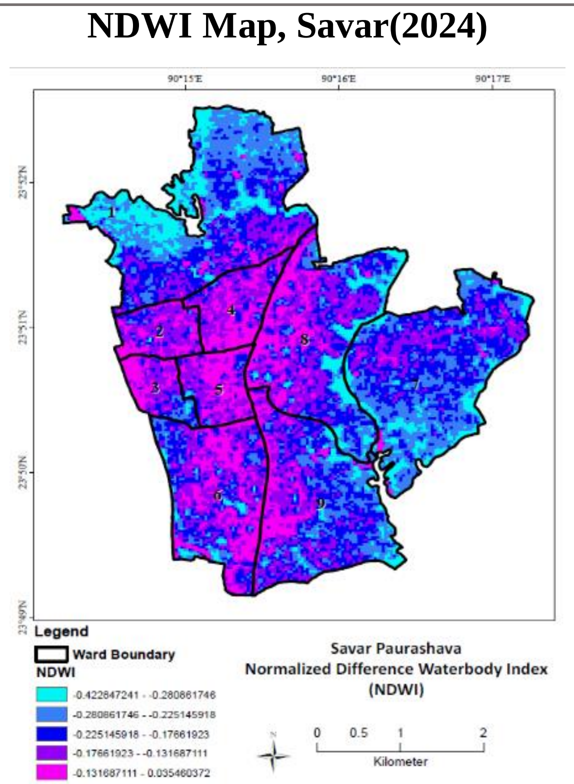


Figure 5: NDWI Map (Source-Authors, 2024)

NDWI values range from negative to positive, with values closer to zero or negative indicating areas with little to no water. Higher NDWI values suggest more prominent water features such as lakes, rivers, ponds, or waterlogged areas. Light Cyan/Aqua in the map figure 4, NDWI values between -0.4228 and -0.2809, indicating minimal or no water presence. These areas are predominantly land with little to no water bodies. Light Blue to Dark Blue shades represent progressively higher NDWI values, indicating areas with increasing amounts of water. As the blues darken, the water presence becomes more substantial. Magenta/Pink Shades are used to represent The highest NDWI values, ranging from -0.1317 to -0.0355, indicate a strong presence of water bodies. The brightest magenta/pink corresponds to the most water-dense areas.

SAVI

The spatial distribution of colors in map (figure 6) reveals which wards have higher or lower vegetation densities. Wards with more dark green and dark blue areas have higher vegetation density and healthier vegetation. Wards dominated by yellow and light green colors have less vegetation cover or more exposed soil. By observing the color distribution, we can identify areas in Savar Paurashava with more vegetation cover versus areas with sparse vegetation. Variations in SAVI values may reflect differences in land use, such as residential areas, agricultural fields, open lands, or urban development zones.

SAVI Map, Savar(2024)

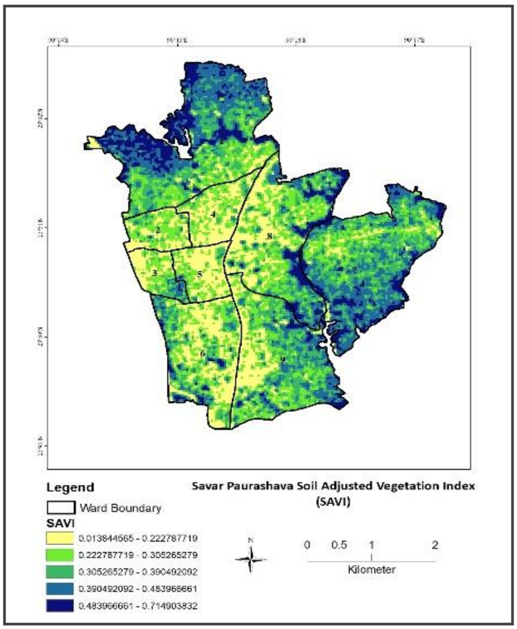


Figure 6: SAVI Map (Source-Authors,2024)

In summary, this map figure 6 offers a detailed view of vegetation distribution within Savar Paurashava, with SAVI values highlighting areas of varying vegetation density. This information can support decisions in urban planning, agriculture, and environmental management.

MNDWI

The darker blue areas in map suggest the presence of water bodies, such as rivers, ponds, or waterlogged zones. Wards with more deep blue regions likely contain higher concentrations of water bodies. Some wards show larger areas of dark blue, indicating more water coverage, while others have mostly lighter blue and cyan shades, reflecting limited water presence. This MNDWI map (fig. 7) can support urban planners and environmental managers by identifying water bodies that need preservation or monitoring, especially in urbanized areas where water resources may be under pressure. In summary, this MNDWI map figure 6 offers insights into water distribution across Savar Paurashava, highlighting areas with different water body densities. This information can be valuable for water resource management, urban development planning, and environmental conservation in the region.

MNDWI Map, Savar(2024)

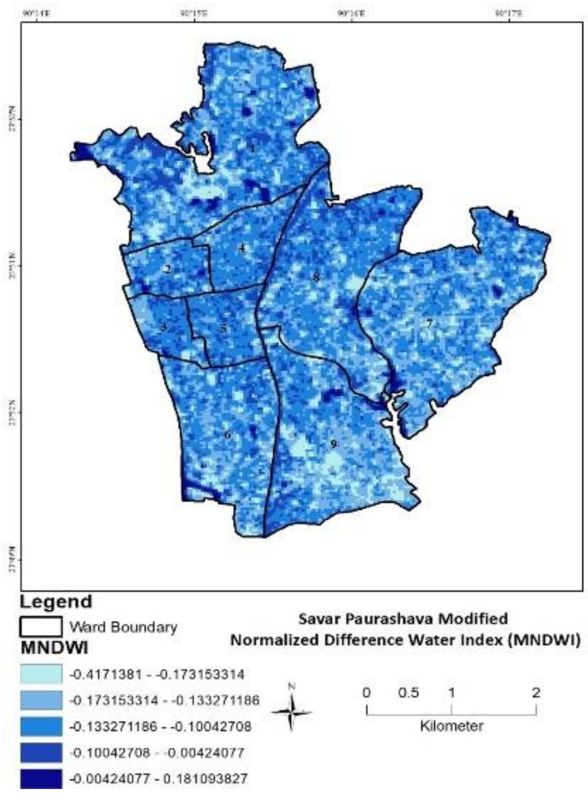


Figure 7: MNDWI Map (Source-Authos,2024)

NDBI

The distribution of colors in map indicates varying degrees of urbanization across the wards. It illustrates that Wards with predominantly darker purple shades have fewer built-up areas, suggesting more vegetation or open land whereas Wards with a mix of green and yellowish-green tones may indicate areas with more developed land use, possibly including residential, industrial, or commercial areas. This map (figure 7) is useful for urban planning and land use analysis in Savar, as it highlights areas of dense and sparse urbanization. It can help local authorities in planning infrastructure, green spaces, and urban expansion based on existing development patterns.

NDBI Map, Savar(2024)

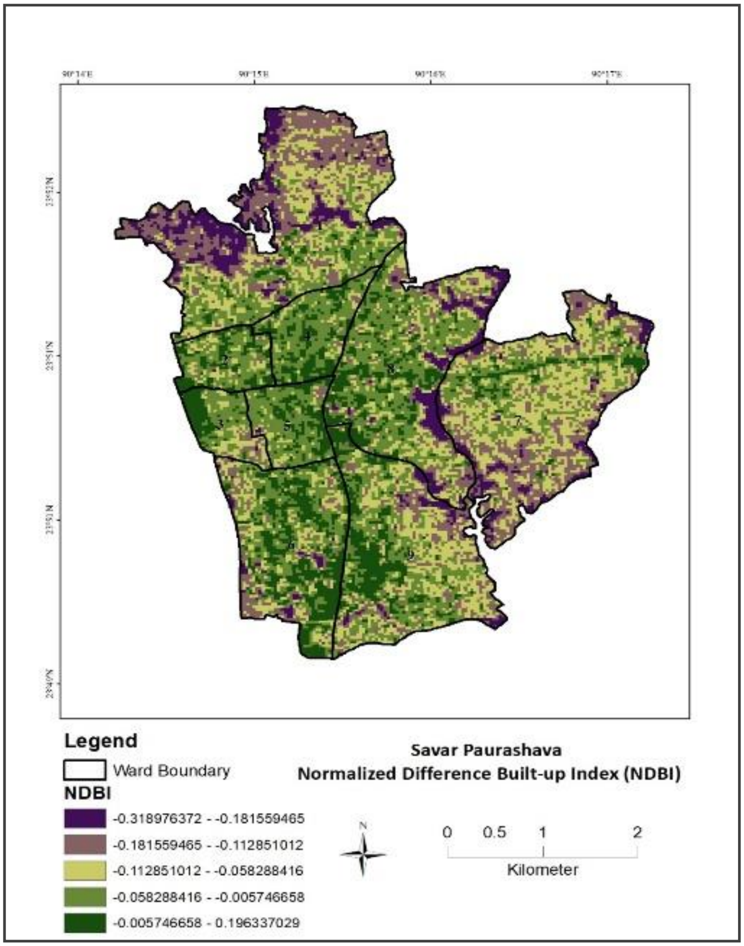


Figure 8: NDBI Map (Source- Authors,2024)

NDMI (figure 9)

This map illustrates the Normalized Difference Moisture Index (NDMI) across the wards of Savar Paurashava. NDMI helps identify moisture levels in vegetation and soil, with higher values generally indicating higher moisture content, while lower values suggest drier areas. The map figure 7 uses a range of purple shades to represent different NDMI values.

NDBI Map, Savar(2024)

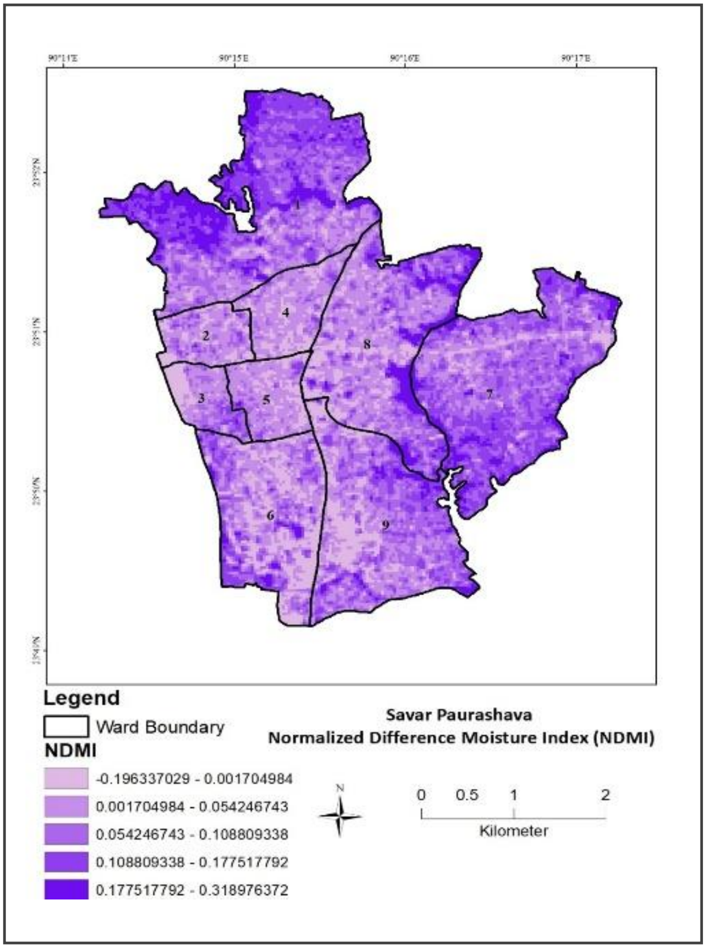


Figure 9: NDMI Map (Source-Authors,2024)

Table 2: List of Color and their explanation

Color Name	Value Range	Explaination
Light Purple	(-0.1963 to -0.0017)	Represents areas with very low NDMI values, indicating minimal moisture content. These regions are likely to be drier, with less vegetation or exposed soil.
Pinkish Purple	(0.0017 to -0.0542)	Slightly higher moisture than the light purple areas, these regions may have some vegetation or soil with limited moisture.
Moderate Purple	(0.0542 to -0.1088)	Areas with moderate moisture levels, possibly indicating a mix of vegetation and bare soil.
Dark Purple	(0.1088 to -0.1775)	Higher NDMI values, likely indicating areas with relatively moist soil and denser vegetation.
Deepest Purple	(0.1775 to -0.3189)	Highest moisture content, likely areas with dense vegetation, wetlands, or areas near water bodies.

This NDMI map (fig 9) highlights the spatial distribution of moisture levels across Savar. Wards with darker purple shades have higher moisture, suggesting the presence of water bodies, vegetation, or areas with retained soil moisture whereas Lighter purple areas have lower moisture content, which could correspond to urban or built-up zones with impervious surfaces, limited vegetation, and less water retention. This information is valuable for environmental management and urban planning, as it helps identify areas of high and low moisture, supporting decisions on irrigation, green space planning, and water resource management in Savar.

Land Use Classification with Corresponding LST and Environmental Indices (NDMI, SAVI, MNDWI, NDBI, NDWI, NDVI)

Land Use	NDMI	SAVI	MNDWI	NDBI	NDWI	NDVI	LST	Normalize_LST
Agricultural Land	0.11	0.40	-0.13	-0.11	-0.24	0.25	30.0	0.12
Residential Area	0.06	0.30	-0.13	-0.06	-0.18	0.18	31.0	0.50
Road Network	0.03	0.25	-0.12	-0.03	-0.15	0.15	31.5	0.72
Open Space	0.10	0.38	-0.13	-0.10	-0.22	0.23	30.3	0.24
Water Bodies	0.13	0.42	-0.12	-0.13	-0.25	0.26	29.7	0.01
Educational Institution	0.04	0.27	-0.13	-0.04	-0.17	0.17	31.1	0.57
Health Facility	0.00	0.18	-0.12	0.00	-0.11	0.12	31.9	0.89
Admin Area	0.11	0.39	-0.12	-0.11	-0.23	0.24	31.0	0.53
Pond	0.03	0.27	-0.14	-0.03	-0.17	0.17	31.7	0.79
Commercial Area	0.02	0.22	-0.13	-0.02	-0.14	0.14	32.1	0.95
Industrial Area	0.02	0.24	-0.13	-0.02	-0.15	0.14	32.2	0.98
River Network	0.06	0.29	-0.12	-0.06	-0.18	0.18	31.5	0.73

Figure 10: LU Classification by Environmental Indicators

Descriptive Statistics

Descriptive statistics is a branch of statistics that involves summarizing, organizing, and interpreting data to highlight its main features. It provides a simple overview of a dataset's central tendency, dispersion, and overall distribution, using measures like the mean, median, mode, standard deviation, and frequency distributions. Descriptive statistics are used to present raw data in a meaningful way, making it easier to understand and interpret the characteristics of a dataset. The central tendency of the data set is described in the Table 3.

Table 3: Central Tendency of the data set.

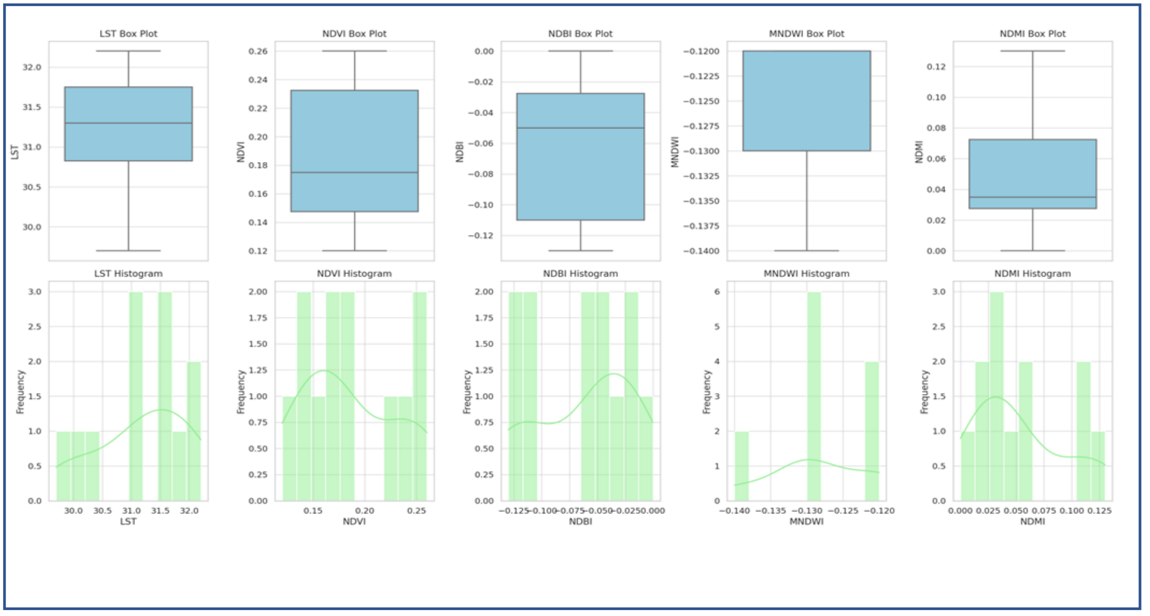
Metric	LST	NDVI	NDBI	MNDWI	NDMI
Count	12	12	12	12	12
Mean	31.17	0.1858	-0.0625	-0.1283	0.0533
Std Dev	0.815	0.0476	0.0460	0.0072	0.0419
Min	29.7	0.12	-0.13	-0.14	0.00
25th %	30.825	0.1475	-0.11	-0.13	0.0275
Median	31.3	0.175	-0.05	-0.13	0.035
75th %	31.75	0.2325	-0.0275	-0.12	0.0725
Max	32.2	0.26	0.00	-0.12	0.13

The central tendency of the data set corresponds to each of the environmental indicators signifies their modulated formation in descriptive statistical analysis. The Mean (Average) for LST is 31.17°C, that indicates a relatively high average temperature across land use types. For NDVI it is 0.1858, showing moderate vegetation density; higher values indicate more vegetation. When it is -0.0625 for NDBI, which is slightly negative, suggesting minimal built-up or urbanized areas. Similarly, for MNDWI, it is -0.1283, a negative value that typically indicates low water content in land cover. But for NDMI: 0.0533, indicating low to moderate moisture levels in the area. Standard Deviation (Std Dev) that Measures how spread out the values are, is different for each of the environmental indicators. For LST, it is 0.815, showing slight temperature variation. But for NDVI it is 0.0476, meaning vegetation density varies only slightly across land types. Again, for NDBI it is 0.0460, suggesting minimal variation in built-up intensity. It is 0.0072 for MNDWI, indicating very low variability in water content. And for NDMI: 0.0419, showing limited variation in moisture levels. The lowest value recorded for each variable is counted as the Minimum (Min). It is also distinguishable for each of the indicators. For LST, it is 29.7°C, the lowest temperature observed. For NDVI, it is 0.12, the minimum vegetation index, suggesting low vegetation density. Consequently, for NDBI it is -0.13, a low value indicating non-built-up or natural areas. It is -0.14 for MNDWI, a negative value indicating no significant water bodies. But for NDMI it is 0.00, meaning very low soil moisture in certain areas. The value below which 25% of data points fall is ascertained by 25th Percentile (25th %). For LST, it is 30.825°C, showing that a quarter of the LST values are below this temperature. And for NDVI it is 0.1475, indicating lower vegetation density in 25% of the land use types. For NDBI, it is -0.11, confirming non-built-up areas in the lowest quarter. Correspondingly for MNDWI it is -0.13, suggesting limited water content in these areas. And for NDMI it is 0.0275, showing low moisture content in the first 25% of data points. The middle value when data is ordered is Median (50th Percentile). For LST, it is 31.3°C, representing the median temperature. For NDVI it is 0.175, the median vegetation index. For NDBI it is -0.05, showing most areas are not built-up. For MNDWI it counts -0.13, confirming low water presence in half the land use types. And for NDMI it is 0.035, indicating moderate moisture levels in the middle of the dataset. The value below which 75% of data points fall is determined by 75th Percentile (75th %) which is 31.75°C for LST, showing that most temperatures are below this value, 0.2325 for NDVI, reflecting higher vegetation density in the top 25% of land use types,-0.0275 for NDBI, with negative values indicating limited urbanization, -0.12 for

MNDWI, further supporting low water features in 75% of areas, and 0.0725 for NDMI, showing higher moisture content in the top 25% of data points. The highest value recorded for each variable is known as the Maximum (Max). It is also not the same for variables. It is 32.2°C for LST that means the maximum temperature observed, 0.26 for NDVI, indicating areas with relatively dense vegetation, but 0.00 for NDBI, suggesting some minimally built-up areas, -0.12 for MNDWI, with no positive values, supporting the lack of significant water bodies and finally 0.13 for NDMI, the highest soil moisture observed, though still low. The data highlights generally high temperatures, moderate vegetation, minimal built-up areas, limited water presence, and low soil moisture across land use types. The low variation in NDBI, MNDWI, and NDMI suggests consistent environmental characteristics, while LST and NDVI show slight variability.

Distribution Analysis

The distribution of each variable within each LULC category, identifying patterns, outliers, and range differences between land cover types is illustrated by Box Plots and Histograms.



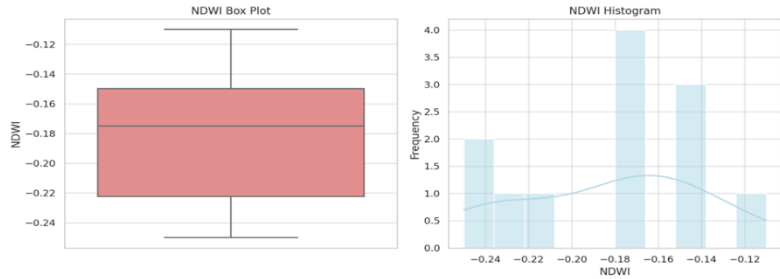


Figure 11: Distribution Pattern of Environmental Indicators.

According to the figure 9, the following observations can be ascertained. Each of the observations are shown in the Table 4.

Table 4: Explanation Environmental Indication

Environmental Indicaton	**Explanation**	
	Box Plot	**Histogram**
LST	LST values are fairly concentrated with minimal spread, indicating relatively consistent temperatures across different land use types. The median is close to the middle of the range, showing a balanced distribution.	LST data shows a slightly right-skewed distribution, with most values around 31°C, suggesting a tendency towards higher temperatures.
NDVI:	NDVI values have a moderate range, reflecting variation in vegetation density across land types. There are no extreme outliers, and the median is slightly below the center, showing a slight left skew.	The distribution is nearly uniform, indicating a mix of vegetation levels across land types without any extreme concentration.
NDBI:	: NDBI values are close to zero, indicating that most land types are not highly built-up. The small spread and slight skew toward negative values suggest that non-built-up areas are more common.	The data is concentrated on the negative side, supporting the presence of more natural or non-built-up areas.

MNDWI:	The range is narrow and consistently negative, suggesting minimal water features, as MNDWI values are more negative in non-water areas.	: Values cluster around -0.13, indicating a limited water presence across land types.
NDMI	NDMI has a broader spread, reflecting variability in soil moisture. There is a mild skew toward lower values.	The distribution is somewhat left-skewed, showing more areas with lower moisture content.
NDWI	NDWI values are consistently negative, indicating low water presence across different land use types. The range is narrow, and there are no outliers, showing uniformity in the dataset.	The distribution is skewed left, with values concentrated around -0.18, which reinforces the minimal presence of water bodies in the studied area.

Correlation Analysis

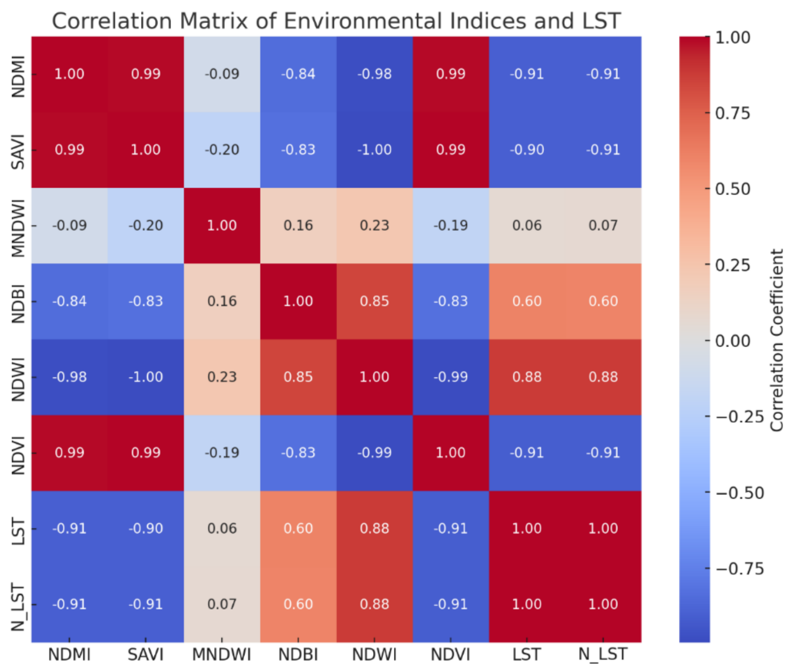


Figure 12: Correlation Analysis

The correlation analysis of the environmental indices and LST data is showed in the heatmap. Here the Positive correlations (in red) indicate that as one variable increases, the other tends to increase as well whereas the Negative correlations (in blue) suggest that as one variable increases, the other tends to decrease.

From the correlation matrix table and heatmap, the following observation :

1. NDMI and NDVI show a strong positive correlation (r = 0.99).
2. NDVI and NDWI are highly negatively correlated (r = -0.99), implying that as vegetation density (NDVI) increases, water availability (NDWI) tends to decrease.
3. LST has a significant positive correlation with NDBI and NDWI, indicating that built-up areas (NDBI) and water bodies (NDWI) are associated with higher LST.
4. LST is negatively correlated with NDMI and NDVI, showing that areas with higher vegetation density (NDVI) tend to have lower temperatures.

Regression Analysis

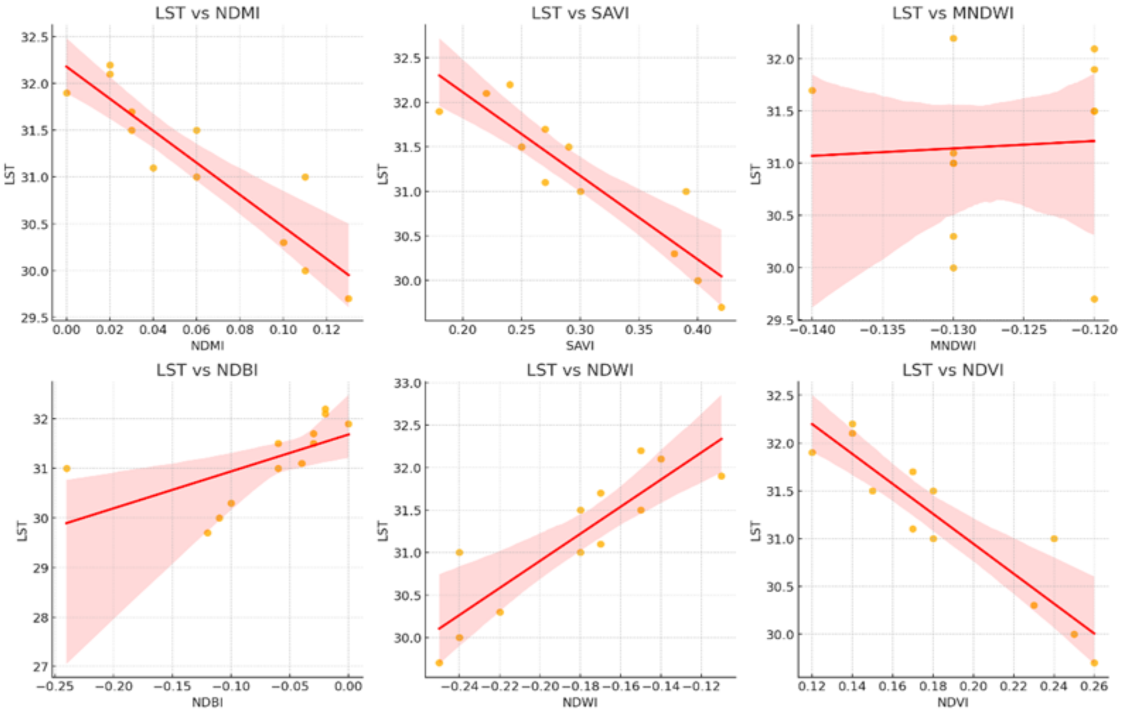


Figure 13: Regression Analysis

The image displays the results of a regression analysis investigating the relationship between Land Surface Temperature (LST) and several vegetation indices: Normalized

Difference Moisture Index (NDMI), Normalized Difference Built-up Index (NDBI), Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), and Normalized Difference Vegetation Index (NDVI). Each subplot shows a scatter plot with a regression line and confidence interval. Each plot follows the same structure, but the X-axis Represents the value of a specific vegetation index (NDMI, NDBI, SAVI, NDWI, NDVI, or MNDWI) , Y-axis Represents the Land Surface Temperature (LST), The Scatter points (orange) indicates Individual data points showing the LST and vegetation index values for different locations or time points, the Red line shows the regression line indicating the best linear fit to the data. It shows the general trend of the relationship and Pink shaded area indicates the confidence interval around the regression line. It represents the uncertainty in the estimated relationship. A wider band indicates more uncertainty.

The slope and direction of the regression line indicate the nature of the relationship.

Negative slope: A negative slope suggests an inverse relationship. As the vegetation index increases, the LST decreases (and vice versa). This is generally expected because healthy vegetation tends to have lower LST due to evapotranspiration cooling. This is observed in the plots for NDMI, SAVI, and NDVI.

Positive slope: A positive slope indicates a direct relationship. As the vegetation index increases, the LST also increases. This might indicate a scenario where higher vegetation indices are associated with different land cover types that retain more heat. This is seen in the plot for NDBI and NDWI.

Near-zero slope: A regression line with a slope close to zero suggests a weak or no linear relationship between the vegetation index and LST. The MNDWI plot shows this.

Specific Index Interpretations

Indicators	**Correlation**
NDMI	Shows a strong negative correlation, indicating that areas with higher moisture content (higher NDMI) tend to have lower LST
NDBI	Shows a positive correlation, suggesting that areas with more built-up areas (higher NDBI) tend to have higher LST due to the urban heat island effect.
SAVI	Shows a strong negative correlation, similar to NDMI, indicating the relationship between vegetation and LST.

NDWI	Shows a positive correlation, suggesting that areas with higher water content (higher NDWI) have higher LST. This might be due to the high heat capacity of water.
NDVI	Shows a strong negative correlation, consistent with the expected relationship between vegetation health and LST.
MNDWI	Shows a very weak or no relationship between LST and moisture content.

In summary, this regression analysis provides insights into the relationships between LST and various vegetation indices. However, it's crucial to consider the limitations and interpret the results within the context of the study area and data used. Further analysis, potentially incorporating non-linear models and additional environmental variables, could provide a more comprehensive understanding.

Overall Finding

Why Built-Up Areas Exhibit High LST

The study reveals that **built-up and industrial zones**, particularly in **Ward-1 and Ward-4**, exhibit the **highest Land Surface Temperatures (LST)** across Savar. This outcome is expected due to the **dominance of impervious materials** like concrete, metal, and asphalt. These materials possess **low albedo**, meaning they absorb a significant portion of solar radiation and retain heat throughout the day, only to slowly release it at night. This retained heat contributes directly to the **Urban Heat Island (UHI) effect**, making these areas substantially warmer than their rural or green counterparts. Another contributing factor is the **lack of vegetation** in these built-up areas. Vegetation plays a crucial role in cooling the environment through **evapotranspiration**, a process where plants release moisture into the air, reducing surface heat. Moreover, vegetation provides **shade**, further decreasing the solar radiation reaching ground surfaces. The near-absence of these natural cooling mechanisms in densely urbanized zones amplifies heat accumulation and leads to consistently high LST readings.

The Role of Vegetation and Water Bodies in Cooling Urban Heat

Vegetation (High NDVI Areas): The findings clearly show that wards with higher vegetation cover—particularly **Ward-7 and Ward-9**—tend to exhibit significantly **lower LST**. These areas scored high on the **Normalized Difference Vegetation Index (NDVI)**, which reflects dense and healthy green cover. Vegetation's **transportational cooling effect**, along with its ability to **shade surfaces**, contributes directly to mitigating urban temperatures.

Water Bodies (High MNDWI Areas): Similarly, areas near **natural water bodies**—indicated by high **Modified Normalized Difference Water Index (MNDWI)** values—also show **lower surface temperatures**. Rivers, ponds, and wetlands have high heat capacities, meaning they absorb solar radiation without rapid increases in temperature. This allows them to act as **natural thermal buffers**, helping to moderate urban heat throughout the day. This pattern strongly affirms the value of **green (vegetation)** and **blue (water bodies)** infrastructure in **climate-responsive urban design**. Their presence significantly reduces local surface temperatures, thus mitigating the impact of rapid urban expansion and industrialization.

Comparison with Existing Studies

Alignment with Global and Regional Research

The findings of this study **align closely** with a wide body of existing literature on urban climate dynamics. For instance, **Weng (2009)** and **Zhang et al. (2018)** concluded that urbanized areas with **high built-up index (NDBI)** values show elevated LST due to the abundance of heat-retaining surfaces. Conversely, areas with **high vegetation index (NDVI)** tend to maintain cooler surface temperatures. Studies conducted in **Dhaka**, **Beijing**, and other fast-growing cities echo similar conclusions—**vegetation helps regulate urban heat**, while excessive urban development raises temperatures. The **strong negative correlation between NDVI and LST**, as well as the **positive correlation between NDBI and LST**, observed in this study, is consistent with these previous works.

Conclusion

This study examined the spatial relationship between Land Surface Temperature (LST) and land cover in Savar, Bangladesh, using environmental indices such as NDVI, NDBI, NDWI, MNDWI, NDMI, and SAVI. Findings revealed that built-up and industrial areas—particularly in Ward-1 and Ward-4—show the highest LST due to the dominance of impervious surfaces and lack of vegetation. Areas with high NDVI and MNDWI values, such as Ward-7 and Ward-9, demonstrated significantly lower LST, highlighting the cooling role of vegetation and water bodies. Strong negative correlations between LST and indices like NDVI, NDMI, SAVI, and NDWI confirm the vital role of green and blue infrastructure in regulating urban temperatures. A positive correlation between LST and NDBI further indicates that the expansion of built-up areas without ecological planning contributes to urban heat intensification. Some unexpected results—such as localized positive correlations between NDWI and LST—suggest that the condition and quality of water bodies (e.g., pollution, depth) also influence thermal behavior. Overall, the study emphasizes the urgent need to integrate environmental considerations into urban planning to mitigate the Urban Heat Island (UHI) effect in fast-growing cities like Savar. Preserving and expanding green and blue spaces, along with adopting sustainable construction practices, is crucial to ensuring climate resilience and improving urban livability.

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