Spatiotemporal Dynamics of Land Surface Temperature and its Correlation with Multispectral Indices in the Urban Environment of Dhaka

Sourav Karmakar[1,*], Asif Raihan[2]

[1] University of Tartu, Tartu, Estonia
[2] National University of Malaysia, Bangi, Malaysia

*Corresponding author's email: karmakersourav@gmail.com

Abstract
Land Surface Temperature (LST) plays a pivotal role in evaluating urban living conditions, particularly in the face of expanding cities and population growth. As urban areas extend both vertically and horizontally, green spaces, open areas, and water bodies are being replaced by built-up structures, leading to elevated LST. This study focuses on Dhaka city, aiming to derive LST and establish relationships with three remote sensing indices: NDVI, NDWI, and NDBI. Landsat 8 data from the summer seasons of 2015, 2018, and 2021 were utilized, employing the LST retrieval mono-window algorithm. Results indicate a substantial +58.73% net change in areas with surface temperatures >32 °C from 2015 to 2018, accompanied by a -5.09% reduction in areas with temperatures <24 °C from 2018 to 2021. NDVI and NDWI values decreased, while NDBI significantly increased from 2015 to 2021. Negative correlations between LST and NDVI were observed, with R^2 values ranging from 0.29 to 0.30, signifying a moderate correlation. Similar to NDVI, NDWI exhibited a negative correlation with LST, with R^2 values ranging from 0.08 to 0.14, indicating a poor correlation. Conversely, a robust correlation was found between LST and NDBI, showing a strong correlation among all three indices, with R^2 values ranging from 0.57 to 0.62. This study underscores the intricate dynamics between LST and urban indices, shedding light on the evolving thermal landscape of Dhaka city. The results emphasize the urgent requirement for promoting green spaces and restraining further urban expansion through environmental regulations. Given Dhaka's existing saturation of built-up areas, the study proposes various green initiatives, including rooftop gardening, revitalizing urban parks and green spaces, and incorporating green elements into commercial spaces, roads, and flyovers. These measures are essential for combating the urban heat island effect and improving the environmental conditions of Dhaka's urban landscapes.

Keywords: Land surface temperature; Urban heat island; Sustainable urban planning, Environmental regulation

1. Introduction

In recent years, rapid urbanization has taken over the big cities around the world due to the increasing demand of burgeoning population for residential, commercial and industrial areas (Dai et al., 2018; Kumari et al., 2018; Guha & Govil, 2022). In 1950, approximately 30% of the global population resided in urban areas. This proportion surged to 54% by 2014 and is projected to further rise to 66% by the year 2050 (Kumari et al., 2018). Compared to the other regions of the world, Asian cities are rapidly growing in recent decades (Ara et al., 2016). Dhaka has been considered one of the most populous and fast-growing mega cities in the world. To accommodate the pressing needs of its thriving economic, commercial, administrative, and employment sectors, the land use in Dhaka is undergoing persistent changes. Green spaces, open areas, and water bodies are being converted into built-up areas to meet the demands of the city's evolving landscape (Kafy et al., 2021). This alteration in the physical landscape leads to the formation of additional impervious surfaces, intensifying the absorption of incident sunlight and consequently causing a rise in Land Surface Temperature (LST) (Kumari et al., 2018). The escalating intensity of LST in several global cities has recently become a pressing concern. According to the Intergovernmental Panel on Climate Change (IPCC), projections indicate a potential rise in the average global LST by 1.4–5.8 °C by 2100 (Kafy et al., 2021). The rise in LST contributes to the Urban Heat Island (UHI) effect, wherein urban areas experience higher temperatures compared to their rural surroundings due to human activities and modifications to the landscape (Ahmed et al., 2013; Guha et al., 2020; Kafy et al., 2021). LST poses risks to human health, increases energy consumption for cooling, and negatively impacts the living environment, affecting biodiversity and contributing to broader climate change patterns. Besides LST plays a crucial role in assessing the ecological well-being of contemporary urban environments and is recognized as a pivotal parameter in urban planning and management (Guha et al., 2020; Guha & Govil, 2022). Hence, monitoring

LST not only helps create more comfortable and resilient urban environments but also contributes to broader efforts in climate adaptation and mitigation.

Recent developments in satellite imageries help provide accurate and reliable LST estimation. Many studies have demonstrated the effectiveness of medium to high resolution satellite imageries for the retrieval of LST across local to global scale (Dang et al., 2020). Most of these studies focused on Landsat observations as Landsat satellites are equipped with Thermal Infrared Sensor (TIRS) that specifically detect the emitted radiation from the Earth's surface, particularly in the thermal infrared range. Land Surface Temperature (LST) exhibits intricate relationships with various remote sensing indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Built-up Index (NDBI). These indices collectively provide valuable insights into the complex interplay between land surface characteristics and temperature dynamics.

Several studies have been conducted on LST and their relationship with Land-use and Landcover (LULC) in Dhaka city, the amount of research concentrated on LST's relationship with multispectral indices is few. Imran et al., (2021) analyzed the impact of LULC on LST and human thermal comfort using Landsat data in 1993, 2007 and 2020. Mia, (2017) correlates LST and Urban Heat Island (UHI) with LULC from 1989 to 2015 using Landsat archives. Rahman et al., (2020) employed TerraSAR-X, ASTER-GDEM and ALOS-based Digital Surface Model (DSM) to investigate vertical growth of Dhaka and relate this with Landsat-derived LST. Raja & Neema, (2013) assessed the impact of urban development and NDVI on LST from the year 1989 to 2010. In their study, Kafy et al., (2021) employed the CA-ANN algorithm to model the relationship between LULC and LST across the years 2000 to 2020, with predictions extending to 2030. However, the use of a 10-year interval in their analysis might be deemed lengthy considering the LST can undergo changes due to climatic factors such as evaporation, precipitation, air temperature and moisture content. While some studies incorporated one or two multispectral indices alongside LULC, very few studies have drawn the correlation of LST with other indices in regards of Dhaka city. To address this gap, this research aims to investigate the spatiotemporal variation of LST and three related indices (NDVI, NDWI and NDBI) from the year 2015 to 2021 with 3 year of interval and drawn the correlation between LST and the indices. The findings can help urban planning, climate resilience strategies, and environmental management, contributing to a more comprehensive understanding of the city's evolving dynamics and supporting the underlying goals of SDG 11 (sustainable cities and communities) and SDG 13 (climate action).

2. Methods

2.1. Study area

This research was carried out within the context of Dhaka, Bangladesh, which stands as one of the world's rapidly growing mega-cities. Located between latitudes 23.58°N and 23.90°N, and longitudes 90.33°E and 90.50°E, Dhaka is situated on the banks of the Buriganga River and is encircled by six rivers. Dhaka is considered as one of the most extensive urban agglomerations, home for over 20 million people, spanning an approximate land area of 304.16 km2 (Kafy et al., 2021). Over the past two decades, the city has experienced a substantial population surge of around 15 million, mainly attributed by rural-urban migration. This demographic expansion has led to both vertical and horizontal expansions in Dhaka, undergoing constant transformation, with open spaces and water bodies being converted into developed areas as a part of the ongoing urbanization process. Consequently, there has been an upward trend in Land Surface Temperature (LST) over the past five decades, characterized by sudden fluctuations in both minimum and maximum temperature levels (Ahmed et al., 2013). The elevation of this region ranges from 1 to 14 meters. Situated in a humid subtropical monsoon climate, the area experiences an annual rainfall of around 2000 mm, with an average yearly precipitation of 114 mm. Dhaka City's climate maintains an average annual temperature of 25 °C, fluctuating from 18 °C in January to 29 °C in August. The study zone encompasses the Dhaka Metropolitan (DMP) area, as depicted in Figure 1.

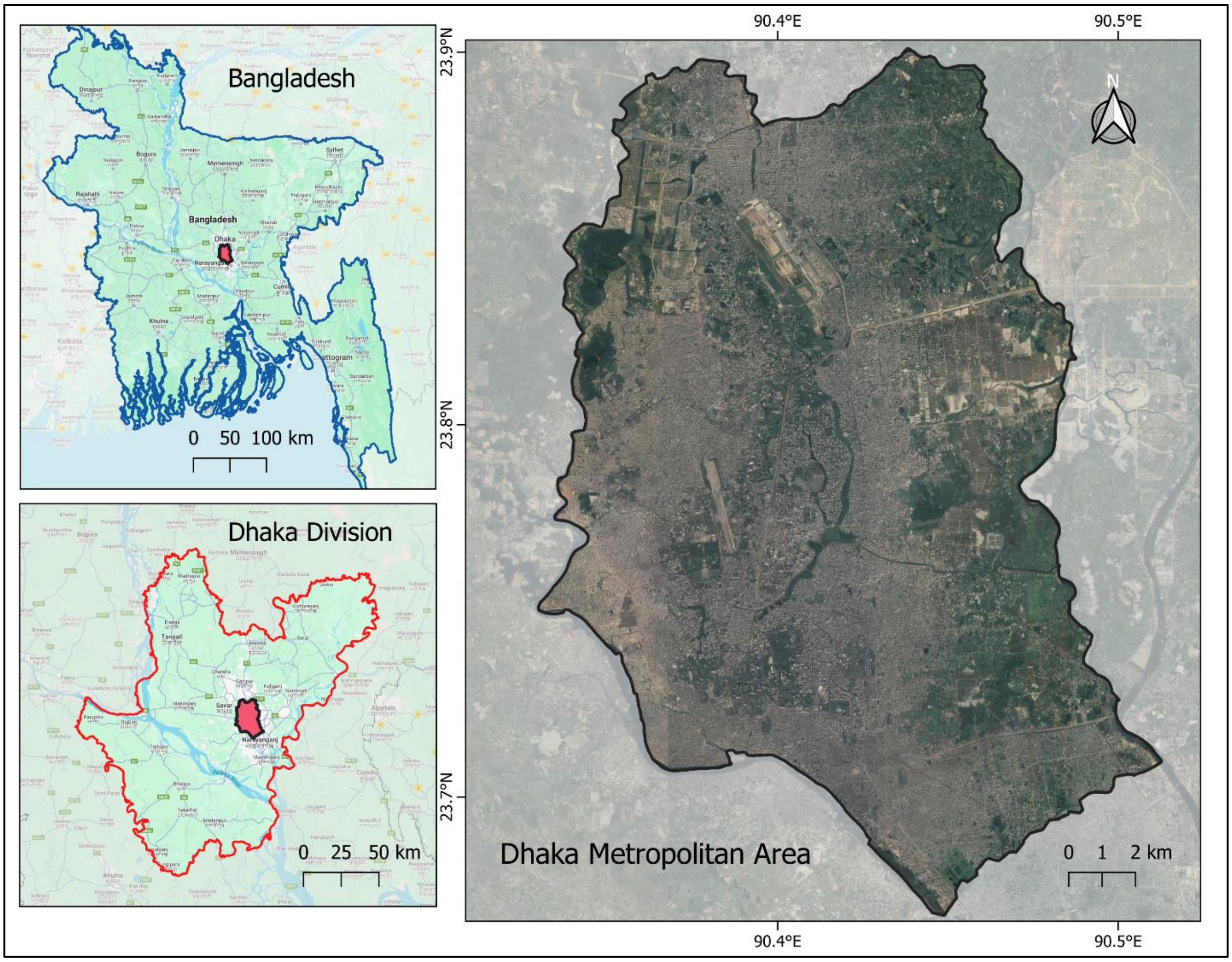

Figure 1. Map of the Study area.

2.2. Dataset

The Landsat satellite series has proven to be effective in prior research due to its inclusion of thermal infrared bands. Landsat datasets are freely accessible on the USGS website (https://earthexplorer.usgs.gov) and are also accessible on the Google Earth Engine as an image collection. For this study, Landsat 8 data for the years 2015, 2018, and 2021 were employed, featuring a spatial resolution of 30 × 30 meters. The study area falls within Landsat path 137, rows 43, and 44. To mitigate the impact of seasonal variations, all images were gathered between March and August annually. Only images with less than 5% cloud cover were included in the study. Subsequently, a median composite was generated from the available image collection to create a single image for each year.

2.3. Retrieval of LST from Landsat 8 data

This study utilized the mono-window algorithm to extract LST from Landsat satellite images, involving key processes such as brightness temperature calculation, fractional vegetation calculation, and emissivity correction (Guha et al., 2020; Shahfahad et al., 2020). The mono-window algorithm incorporates several equations to determine LST. Initially, the top-of-atmosphere (TOA) reflectance was used to derive brightness temperature, employing calibration constants outlined in metadata (Chander et al., 2009). Subsequently, emissivity correction was executed through the NDVI threshold method (Sobrino et al., 2004). Fractional vegetation was then computed using the methodology described by Carlson & Ripley, (1997) based on NDVI. The land surface emissivity, factored by fractional vegetation, was further determined. Finally, LST was calculated using the following equation (Kafy et al., 2021).

$$\mathrm{LST} = \frac{T_i}{1 + \left(\lambda \times \frac{T_i}{\rho}\right) \times \ln(\varepsilon)}$$

Here, T_i represents the brightness temperature of the sensor, λ denotes the wavelength of the emitted radiance, and Ɛ represents the spectral emissivity of the land surface. Additionally, $\rho = hc / \sigma = 1.438 \times 10^{-2}$ mk, where h is Plank's constant (6.626×10^{-34} Js), c is the velocity of light (2.998×10^{8} ms^{-2}) and σ is the Boltzmann constant (5.67×10^{-8} $\mathrm{Wm}^{2}\mathrm{k}^{-4} = 1.38 \times 10^{-23}$ JK^{-1}). Finally, to convert LST to Celsius, subtracting 273 was performed in the last step.

2.4. Spectral indices calculation

Three spectral indices namely NDVI, NDWI and NDBI were used in this study, summarized in Table 1. NDVI is most commonly used for vegetation distribution and density. It is calculated from red and near infrared bands due to their highest absorption of electromagnetic energy by chlorophyll. As vegetation plays an important role in surface emissivity and surface energy balance, it influences the LST. The NDWI is commonly employed to extract water surfaces, calculated from green and near infrared bands, offering insights into the complex dynamics between water features and land temperature. NDBI is used for determining the built-up areas which is crucial in understanding the impact of built-up regions on surface temperature.

Table 1. Multispectral indices used in this study.

Name	**Formula**	**Landsat 8 bands**	**References**
Normalized Difference Vegetation Index (NDVI)	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$	$\frac{\mathrm{B5} - \mathrm{B4}}{\mathrm{B5} + \mathrm{B4}}$	(Tucker, 1979)
Normalized Difference Water Index (NDWI)	$\mathrm{NDWI} = \frac{\mathrm{Green} - \mathrm{Red}}{\mathrm{Green} + \mathrm{Red}}$	$\frac{\mathrm{B3} - \mathrm{B4}}{\mathrm{B3} + \mathrm{B4}}$	(McFeeters, 1996)
Normalized Difference Built-up Index (NDBI)	$\mathrm{NDBI} = \frac{\mathrm{SWIR} - \mathrm{NIR}}{\mathrm{SWIR} + \mathrm{NIR}}$	$\frac{\mathrm{B6} - \mathrm{B5}}{\mathrm{B6} + \mathrm{B5}}$	(Zha et al., 2003)

2.5. Correlation analysis

The annual computation of Land Surface Temperature (LST) and multispectral indices was performed, after which the entire study area was divided into a grid of 500*500 square units. A centroid was generated for each grid, establishing a fixed set of points. Subsequently, raster values for LST, NDVI, NDWI, and NDBI were sampled at these persistent points. This systematic approach ensured consistency over time. The next step involved conducting a correlation analysis based on the values obtained from these fixed points, providing insights into the relationships between LST and various multispectral indices across the study area.

3. Results and Discussion

Landsat thermal bands were used to determine the areal distribution of LST trends in summer seasons from 2015 to 2021 (Figure 2). The color tone orange to reddish indicates lower to higher temperatures of the study area for all the years. In the year 2015, greater temperatures were observed in the city's western to southern areas, which were expanded from 2018 to 2021. By 2021, significant patches of reddish areas emerged i.e., rapid LST change occurred in the north to north-eastern parts of the capital. The results showed a + 58.73% net change in the amount of areas with surface temperature > 32 °C, whilst areas with surface temperature less than 24°C reduced by a – 5.09%, from 2018 to 2021.

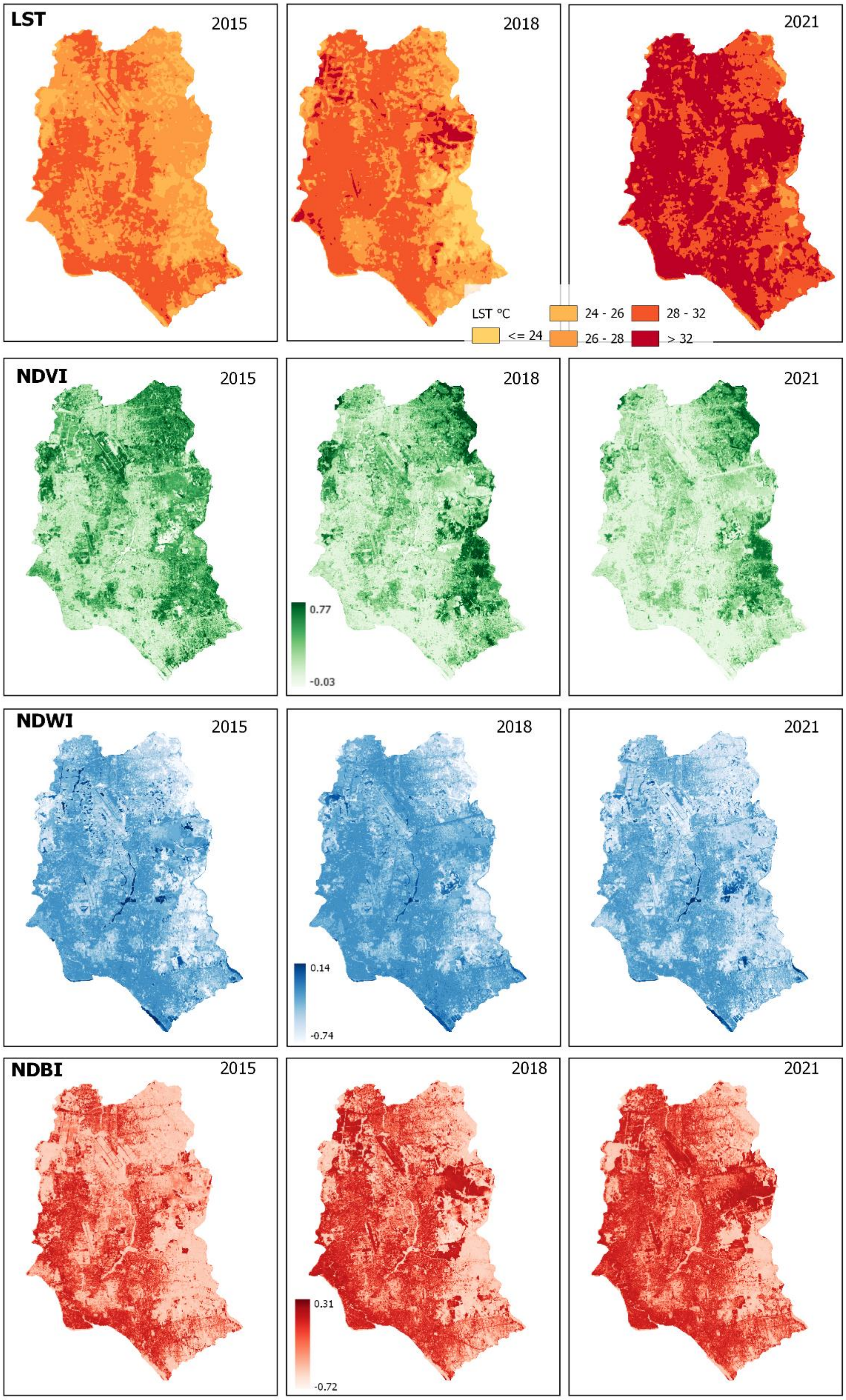

Figure 2. LST, NDVI, NDWI, NBDI in 2015, 2018 and 2021.

Table 2 shows the LST areal distribution throughout the summer season (2015, 2018, and 2021) in five distinct temperature zones. The findings indicated that in 2015, three temperature zones (24 °C - < 26 °C, 26 °C - < 28 °C, and 28 °C - < 32 °C) encompassed the majority of the study area. No area was under less than 24°C, only 0.07% area was detected in the highest temperature zone (≥ 32 °C) during 2015. Meanwhile, in 2018, LST was found at every five class, with a 5.09% area covered by less than 24°C and 3.80% area experienced more than 32 °C. Whereas in the year 2021, 178.27km^2 area fell under the zone of >32 °C which constitutes 58.93% of total areas. No LST was recorded below 26°C during the year 2021. The projected result revealed that in the study area, a lower temperature zone was recorded in 2015 and was transformed into a higher temperature zone between 2018 and 2021.Similar trend has been observed in terms of multispectral indices. Regarding the NDVI, greenest pixel has been reduced from 2015 to 2021. In the central DMP, areas with higher NDVI were observed during 2015 which sequentially reduced from 2018 to 2021. In terms of NDWI, overall, the areas with higher NDWI values reduce over the expanse of 6 years. In the north-western part of the DMP, we found some waterbodies in 2015, which has experienced a reduction in 2021. Lower NDWI in 2021 refers to the reduction in waterbodies, representing waterbodies has been filled in with built areas over the study period. On the other hand, in terms of NDBI, DMP experienced higher built-up areas in the eastern and southern part in 2021. From 2015 to 2021, NDBI has been observed to be increased throughout the study area which represents the increase of buildings and pavements in 2021.

Table 2. Area covered by LST in different years.

LST	**2015 (area)**	**% of total**	**2018 (area)**	**% of total**	**2021 (area)**	**% of total**
<=24	0.00	0.00	15.41	5.09	0.00	0.00
24-26	43.58	14.41	32.00	10.58	0.00	0.00
26-28	154.42	51.05	81.14	26.82	8.81	2.91
28-32	104.31	34.48	162.46	53.70	115.43	38.16
>32	0.20	0.07	11.51	3.80	178.27	58.93
Total	302.52	100.00	302.52	100.00	302.52	100.00

A correlation analysis was carried out in this study to observe the relationship between LST and other multispectral indices within the DMP area (Figure 3). There has been observed a negative correlation between LST and NDVI. The R^2 value ranges from 0.29 to 0.30 which represents a moderate correlation among these two variables. This is quite easily understandable as the values of NDVI range from dense to sparse vegetation and often bare land. Dense vegetated areas give higher values of NDVI in spatiotemporal analysis. Therefore, the higher the vegetation, the less the temperature. Hence, LST is negatively proportionate to NDVI. Another reason can be stated as the greenery (plants and trees) are usually absorbers and evaporators. They discharge water as vapor which results in heat trapping (Kikon et al., 2016). Likewise, NDVI, the NDWI also depicts a negative correlation with LST. The R^2 value was observed 0.08 to 0.14 from 2015 to 2021 representing a poor correlation. Waterbody produces a cooling effect in the temperature therefore reduces the LST. However, in terms of whole urban area the NDWI correlation could be poor and insignificant, but negative correlation has been significantly observed within the waterbody surfaces (Guha & GoviL, 2021). On the other hand, a strong correlation was observed between LST and NDBI. With an R2 ranging from 0.57 to 0.62, it represents the strong correlation among all indices. Additionally, the level of significance and correlation coefficients have been found to be increased with expanse of year. This result represents the reduction in greenery and transformation of green area to built-up areas within Dhaka city from 2015 to 2021.

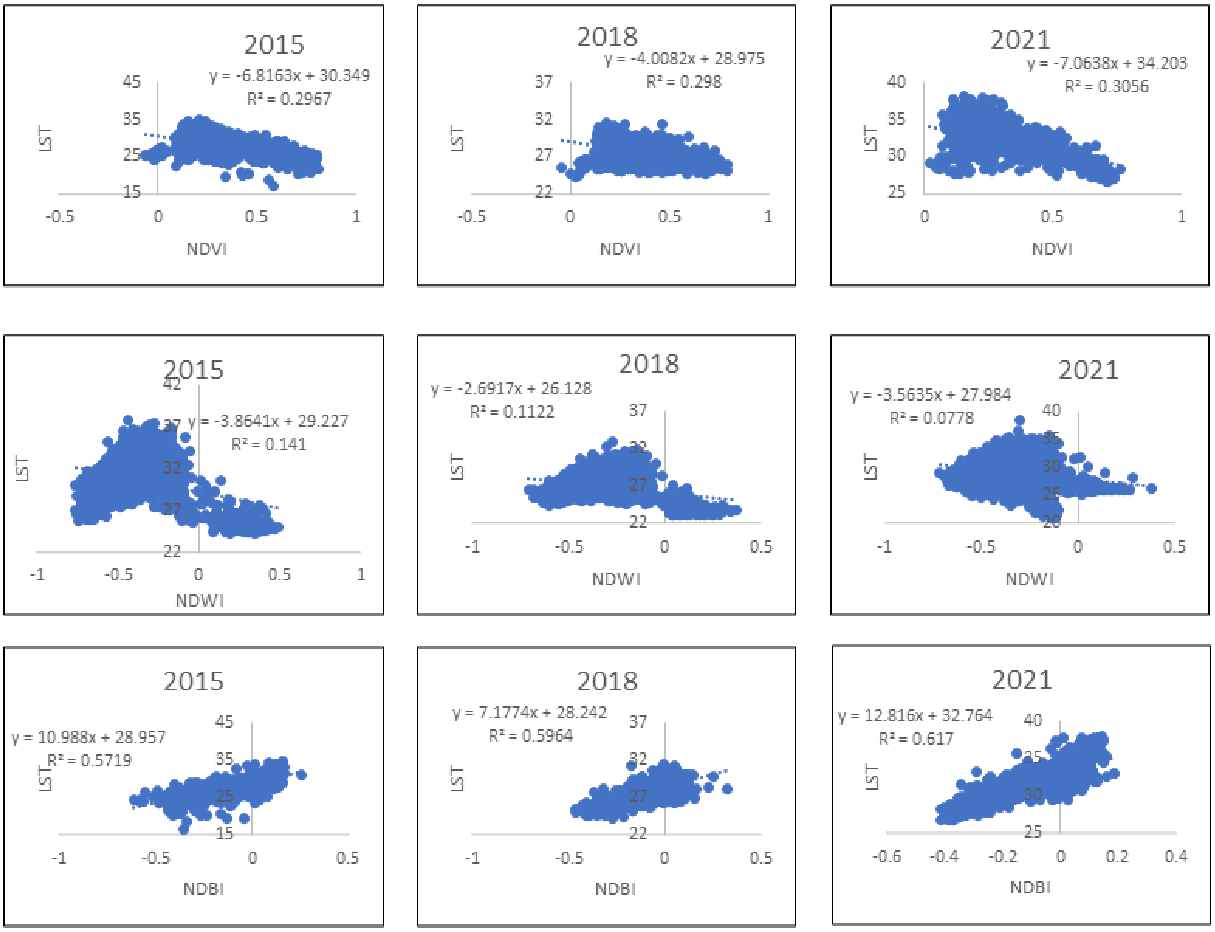

Figure 3. Correlation of multispectral indices with LST.

The result is reliable and significant compared to the other similar studies using Landsat data conducted on Dhaka and other cities from different parts of the world in recent years (Ara et al., 2016; Guha et al., 2020; Kafy et al., 2021). Most of the study observed negative correlation between LST and NDVI and strong positive correlation between LST and NDBI. Regarding the NDWI different result has been observed. Some studies found poor positive correlation while others observed poor negative correlation. Some other studies argued that, for finding good correlation with NDWI, it is recommended to extract waterbodies by using the NDWI values and then correlate it with LST.

4. Conclusion

In conclusion, this research unveils the spatiotemporal dynamics of Land Surface Temperature (LST) and its correlations with various multispectral indices. Over the 2015-2021 period, a noteworthy 58% of the total Dhaka Metropolitan (DMP) areas experienced an elevation in temperature zones, potentially influenced by a decline in NDVI and NDWI alongside a notable surge in NDBI. These findings suggest an overall reduction in vegetation and water bodies, coupled with an increase in built-up areas. The study aligns with prior literature highlighting the unplanned and inadequately monitored expansion of Dhaka city.

This study underscores the critical need for strategic planning and environmental regulatory measures by Dhaka City Corporation and relevant government entities to safeguard the city's cultural and environmental heritage. Urgent actions are required to promote green spaces, curb further urban sprawl, and integrate sustainable practices into urban development initiatives. Initiatives such as rooftop gardening, rejuvenation of urban parks and green spaces, and incorporation of green elements into infrastructure are essential steps toward mitigating the urban heat island effect and enhancing the overall environmental quality of Dhaka's urban landscapes. The insights derived from this research offer valuable guidance for urban planners, facilitating the identification of priority zones experiencing significant alterations in land cover and temperature regimes. By aligning with Sustainable Development Goal 11 (SDG 11) for sustainable cities and communities, strategic planning informed by these findings can contribute to fostering resilient and livable urban environments. Moreover, the understanding of LST dynamics aids in advancing SDG 13, promoting climate action to ensure inhabitants experience comfortable living conditions. Looking ahead, future research endeavors should integrate comprehensive Land Use and Land Cover (LULC) analyses to provide a more nuanced understanding of the specific land cover types driving variations in land surface temperature. Additionally, interdisciplinary collaborations between researchers, policymakers, and community stakeholders are imperative for implementing evidence-based interventions aimed at fostering sustainable urban development and enhancing the resilience of Dhaka city in the face of ongoing environmental challenges.

References

Ahmed, B., Kamruzzaman, M., Zhu, X., Rahman, M. S., & Choi, K. (2013). Simulating Land Cover Changes and Their Impacts on Land Surface Temperature in Dhaka, Bangladesh. *Remote Sensing*, *5*(11), Article 11. https://doi.org/10.3390/rs5115969

Ara, S., Islam, M. A., & Showkat, S. (2016). Effect of land-use intensity on surface temperature: A study on Chittagong city corporation area. *2016 5th International Conference on Informatics, Electronics and Vision (ICIEV)*, 72–77. https://ieeexplore.ieee.org/abstract/document/7759971/

Carlson, T. N., & Ripley, D. A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sensing of Environment*, *62*(3), 241–252.

Chander, G., Markham, B. L., & Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment*, *113*(5), 893–903.

Dai, Z., Guldmann, J.-M., & Hu, Y. (2018). Spatial regression models of park and land-use impacts on the urban heat island in central Beijing. *Science of the Total Environment*, *626*, 1136–1147.

Dang, T., Yue, P., Bachofer, F., Wang, M., & Zhang, M. (2020). Monitoring Land Surface Temperature Change with Landsat Images during Dry Seasons in Bac Binh, Vietnam. *Remote Sensing*, *12*(24), Article 24. https://doi.org/10.3390/rs12244067

Guha, S., & GoviL, H. (2021). Relationship between land surface temperature and normalized difference water index on various land surfaces: A seasonal analysis. *International Journal of Engineering and Geosciences*, *6*(3), 165–173. https://doi.org/10.26833/ijeg.821730

Guha, S., & Govil, H. (2022). Annual assessment on the relationship between land surface temperature and six remote sensing indices using landsat data from 1988 to 2019. *Geocarto International*, *37*(15), 4292–4311. https://doi.org/10.1080/10106049.2021.1886339

Guha, S., Govil, H., & Besoya, M. (2020). An investigation on seasonal variability between LST and NDWI in an urban environment using Landsat satellite data. *Geomatics, Natural Hazards and Risk*, *11*(1), 1319–1345. https://doi.org/10.1080/19475705.2020.1789762

Imran, H. M., Hossain, A., Islam, A. K. M. S., Rahman, A., Bhuiyan, M. A. E., Paul, S., & Alam, A. (2021). Impact of Land Cover Changes on Land Surface Temperature and Human Thermal Comfort in Dhaka City of Bangladesh. *Earth Systems and Environment*, *5*(3), 667–693. https://doi.org/10.1007/s41748-021-00243-4

Kafy, A.-A., Al Rakib, A., Akter, K. S., Jahir, D. M. A., Sikdar, M. S., Ashrafi, T. J., Mallik, S., & Rahman, M. M. (2021). Assessing and predicting land use/land cover, land surface temperature and urban thermal field variance index using Landsat imagery for Dhaka Metropolitan area. *Environmental Challenges*, *4*, 100192.

Kumari, B., Tayyab, M., Shahfahad, Salman, Mallick, J., Khan, M. F., & Rahman, A. (2018). Satellite-Driven Land Surface Temperature (LST) Using Landsat 5, 7 (TM/ETM+ SLC) and Landsat 8 (OLI/TIRS) Data and Its Association with Built-Up and Green Cover Over Urban Delhi, India. *Remote Sensing in Earth Systems Sciences*, *1*(3), 63–78. https://doi.org/10.1007/s41976-018-0004-2

McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, *17*(7), 1425–1432. https://doi.org/10.1080/01431169608948714

Mia, M. (2017). Correlation and Monitoring of Land Surface Temperature, Urban Heat Island with Land Use-Land Cover of Dhaka City Using Satellite Imageries. *International Journal of Research in Geography*, *3*, 10–20. https://doi.org/10.20431/2454-8685.0304002

Rahman, M. M., Avtar, R., Yunus, A. P., Dou, J., Misra, P., Takeuchi, W., Sahu, N., Kumar, P., Johnson, B. A., Dasgupta, R., Kharrazi, A., Chakraborty, S., & Agustiono Kurniawan, T. (2020). Monitoring Effect of Spatial Growth on Land Surface Temperature in Dhaka. *Remote Sensing*, *12*(7), Article 7. https://doi.org/10.3390/rs12071191

Raja, D. R., & Neema, M. N. (2013). Impact of Urban Development and Vegetation on Land Surface Temperature of Dhaka City. In B. Murgante, S. Misra, M. Carlini, C. M. Torre, H.-Q. Nguyen, D. Taniar, B. O. Apduhan, & O. Gervasi (Eds.), *Computational Science and Its Applications – ICCSA 2013* (pp. 351–367). Springer. https://doi.org/10.1007/978-3-642-39646-5_26

Shahfahad, Kumari, B., Tayyab, M., Ahmed, I. A., Baig, M. R. I., Khan, M. F., & Rahman, A. (2020). Longitudinal study of land surface temperature (LST) using mono- and split-window algorithms and its relationship with NDVI and NDBI over selected metro cities of India. *Arabian Journal of Geosciences*, *13*(19), 1040. https://doi.org/10.1007/s12517-020-06068-1

Sobrino, J. A., Jiménez-Muñoz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from LANDSAT TM 5. *Remote Sensing of Environment*, *90*(4), 434–440. https://doi.org/10.1016/j.rse.2004.02.003

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, *8*(2), 127–150.

Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, *24*(3), 583–594. https://doi.org/10.1080/01431160304987