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Measuring Seasonal Variation of Land Use and Land Cover Indices and Its Impact on Land Surface Temperature in Dhaka, Bangladesh

Abstract

Rapid urbanization is anticipated to drive land use and land cover (LULC) changes that increase land surface temperatures (LST) in Dhaka, Bangladesh. This study will aim to analyze seasonal LST variations in relation to LULC indices, emphasizing the need for mitigating urban heat island effects to support sustainable living. The results are expected to show that built-up areas will experience the highest LST values, while vegetation-covered areas will have the lowest. It is also anticipated that there will be a strong inverse correlation between LST and indices such as NDVI and MNDWI, alongside positive correlations with NDBI and NDBAI. A decrease in vegetation and an increase in built-up areas are projected to be primary contributors to LST rises. This approach aims to provide a cost-effective methodology for monitoring LST hotspots and informing urban planning strategies for sustainable development.

Abbreviation: Land use and land cover (LULC), Land surface temperatures (LST), Normalized difference built-up index (NDBI), Modified Normalized Difference Water Index (MNDWI), Normalized Difference Bareness Index (NDBaI), Normalized difference vegetation index (NDVI)

Introduction

Climate and land use are closely linked, with changes in land use and land cover (LULC) both affecting and being affected by climate across various temporal and spatial scales. Improper LULC change, especially in urban areas, is a leading cause of climate change (Mondal et al. 2021; Thakur, Mondal, et al. 2021). Rising land surface temperatures (LST), driven by both human and natural causes, have become a critical urban issue, linked to reduced comfort, poorer air and water quality, increased mortality, and indirect economic losses (Kafy et al. 2022; Steeneveld et al. 2018).

LULC changes can occur because of both human and climate-related factors. Expanding settlements often lead to the permanent loss of natural land cover, affecting local weather, precipitation, and temperature patterns (Morshed et al. 2022; Thakur, Maity, et al. 2021). The shift towards built-up areas diminishes eco-friendly land covers like forests, vegetation, and waterbodies, impacting ecosystems and carbon storage (Kumar, Mondal, and Pham 2021). Although LULC change impacts cities worldwide, the effects are more intense in developed areas, with growing concern from scientists, health authorities, and urban planners over its implications on health, energy demand, and vegetation cycles (Lemonsu et al. 2013; Li et al. 2017; Lowe 2016).

While previous research has explored the LST impacts of LULC in major Bangladeshi cities (e.g., Dhaka, Chittagong), most focus solely on summer variation and skip winter variation. Water bodies and bare land are frequently overlooked. A limited number of studies explored the influence of all LULC types on LST dynamics. Common indices like NDVI and NDBI, though frequently used, often overlook other land covers (NDBaI, NDWI, MNDWI) (Huang and Cadenasso 2016).

This study will address these gaps by analyzing historical LULC and LST trends, and the seasonal and spatial distribution of LULC, LST, NDVI, NDBAI, MNDWI, and NDBI from 2000 to 2020 in Dhaka City. The findings aim to offer insights for urban planners and policymakers to craft effective mitigation strategies in urban development.

Objective

The objective of this study is to analyze historical trends and seasonal distributions of LULC, LST, and land use indices (NDVI, NDBaI, MNDWI, NDBI) from 2000 to 2020 in Dhaka, and to assess seasonal LST changes relative to these indices to guide urban planning and mitigation efforts.

Research Question

- How do seasonal dynamics of LULC indices affect LST in Dhaka?
- What specific changes have occurred in built-up areas, vegetation cover, and LST over time?
- How are different LULC indices correlated with LST?
- What are the implications of these findings for mitigating LST hotspots and preserving ecological balance?

Study Area

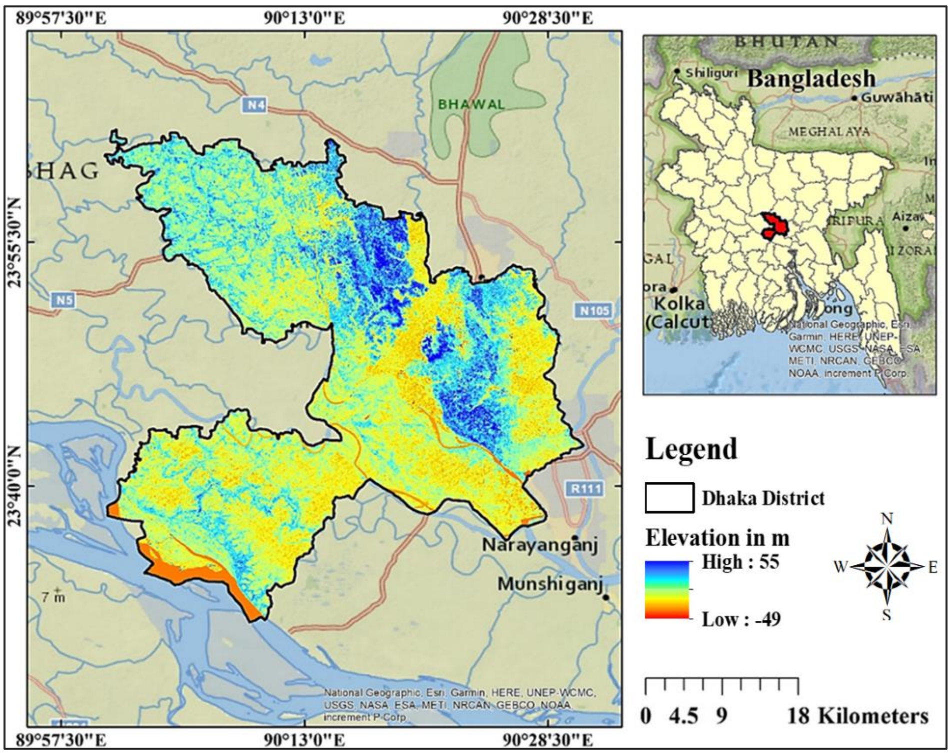


Figure 1: Study Area Map

Methodology

Data Collection

To identify spatial and temporal variations for summer and winter, Landsat images will be collected, using Landsat Collection 1 Level 1 data. ArcGIS 10.8/pro will be employed to process and analyze these images, extracting LST, LULC types, and land use indices through GIS-based remote sensing. Finally, the regression model will be created using python.

Land Use Indices Calculation Procedure

Normalized difference built-up index (NDBI)

NDBI quantifies built-up area concentration by calculating a ratio between near-infrared (NIR) (band 5 for Landsat 8, band 4 for Landsat 5) and shortwave infrared (SWIR) (band 6 for Landsat 8, band 5 for Landsat 5) radiation captured by Landsat sensors (Zhang et al. 2016).

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

NDBI values range from -1 to 1. The higher the value, the more developed area, metro area, or created territory exists.

Modified Normalized Difference Water Index (MNDWI)

MNDWI will be used to the enhancement of open water features, the MNDWI employs pixel values from green (band 3 for Landsat 8 and band 2 for Landsat 5) and short-wave infrared (SWIR) bands (band 6 for Landsat 8 and band 5 for Landsat 5) (Das et al. 2021). It also reduces built-up area characteristics that are commonly linked to water in other indexes. The MNDWI estimation ranges from -1.0 to +1.0.

$$\mathrm{MNDWI} = \frac{(\mathrm{Green} - \mathrm{SWIR})}{(\mathrm{Green} + \mathrm{SWIR})}$$

Normalized Difference Bareness Index (NDBaI)

NDBaI was suggested by Chen et al. (2006) to distinguish bare land from other land uses (NDBaI). The range of the NDBaI estimation is -1.0 to +1.0 (Chen et al. 2006).

$$\mathrm{NDBaI} = \frac{((\mathrm{SWIR\ Band1} - \mathrm{TIRS\ Band\ 1}))}{(\mathrm{SWIR\ Band1} + \mathrm{TIRS\ Band\ 1})}$$

Normalized difference vegetation index (NDVI)

Pixel values from the Landsat Near-Infrared (band 5 for Landsat 8 and band 4 for Landsat 7) and Red (band 4 for Landsat 8 and band 3 for Landsat 5 image) spectral bands will be employed to identify the NDVI (Grigoraș and Urițescu 2019). NDVI is calculated as-

$$\mathrm{NDVI} = \frac{(\mathrm{NIR\ Band} - \mathrm{Red\ Band})}{(\mathrm{NIR\ Band} + \mathrm{Red\ Band})}$$

Land Surface Temperature (LST) Calculation Process

LST is the radioactive temperature of earth surface which is critical for understanding the basic science of the land surface via the energy cycle and aquatic exchange with the environment (Ahmed et al. 2013; Zhang et al. 2013). LST analysis using satellite thermal data entails a variety of procedures, including sensor radiometric alignment, correction of air and surface reflectance and spatial variation of LULC. For calculating LST thermal band 11 (for Landsat 8) and thermal band 6 (for Landsat 5) will be utilized.

$$LST = [\frac{TB}{1 + \left(\frac{\lambda \times TB}{\alpha}\right)\ln \varepsilon}]$$

Correlation Analysis

To determine the interlinkage between two different variables or variable of interest correlation analysis is very effective. So, for assessing the nexus between land use indices and LST, regression models namely linear regression, Pearson's correlation coefficient (Pr) will be calculated using: x_i = values of the x-variable in a sample, x' = mean of the values of the x-variable y_i = values of the y-variable in a sample and y' = mean of the values of the y-variable (Isaac 2018).

$$Pr = \frac{\sum(x_i - x')(y_i - y')}{\sqrt{\sum(x_i - x')^2 \times (y_i - y')^2}}$$

Spearman's rank correlation coefficient (SC) (Sedgwick, 2014) will also be calculated for all the seasons and years. Where d_i = difference between the two ranks of each observation, n = number of observations.

$$SC = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)}$$

The correlation analysis will be conducted in Python using Jupyter Notebook, applying regression models to assess relationships between land use indices and LST. Linear regression and Pearson's correlation coefficient (Pr) will be calculated based on x_i and y_i values and their means x' and y'. Additionally, Spearman's rank correlation coefficient (SC) will be computed for all seasons and years (equation 18). Python libraries, such as Pandas, NumPy, and SciPy, will facilitate the calculations and data handling, ensuring efficient analysis and visualization.

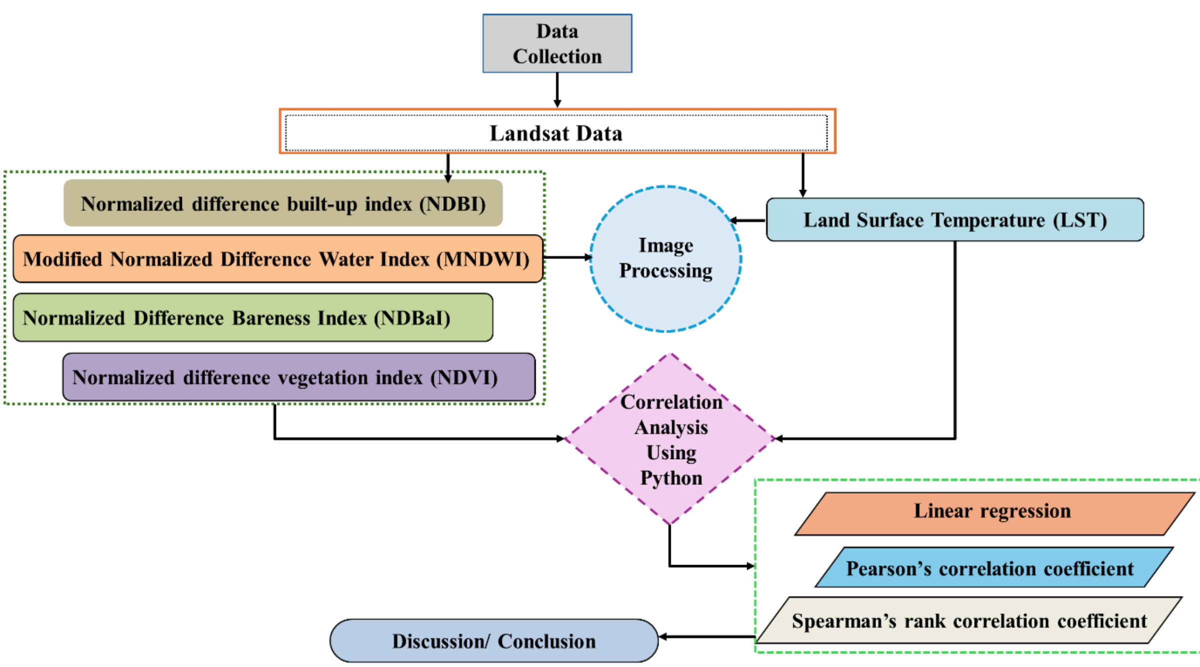


Figure 2: Methodological Framework

Expected Outcome

- Significant expansion of built-up areas, replacing agricultural land and vegetation, with faster urban growth in suburban areas than in the city center.
- Upward trend in surface temperatures over time, with higher increases in summer than in winter, linked to urbanization.
- Inverse correlation between indices for water bodies and vegetation with LST; positive correlation between indices for built-up and bare land with LST, indicating their contribution to higher temperatures.
- Shift towards a greater proportion of higher-temperature areas, with a decrease in cooler areas, showing expansion of warmer zones in the district.
- Declining vegetation cover significantly impacts rising LST, with urban expansion reinforcing this trend.

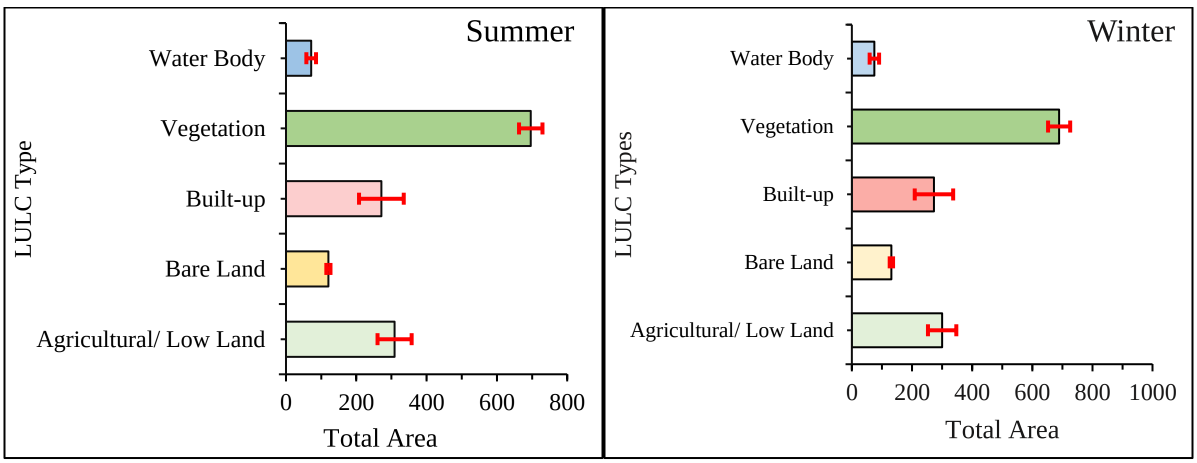
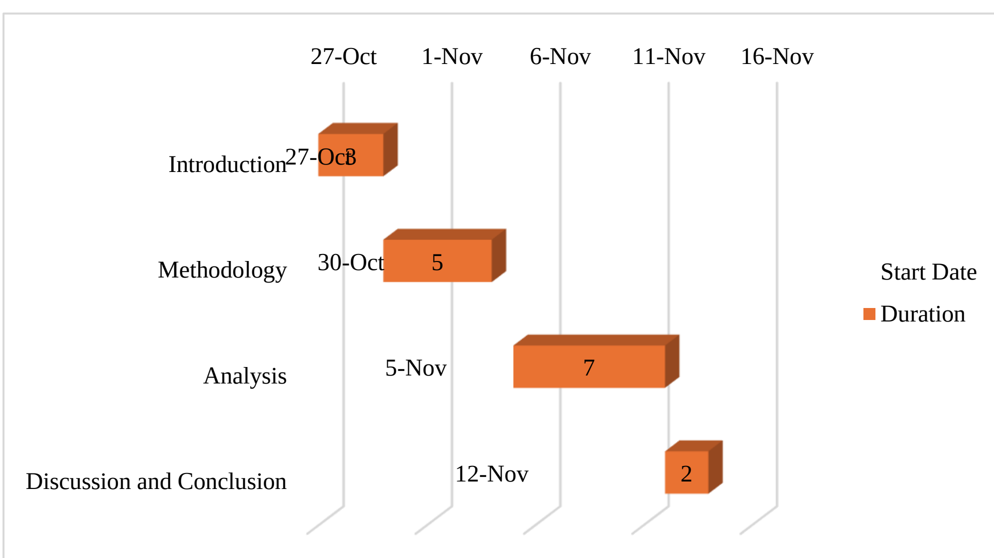


Figure 3: Expected Changes in Land Use Land Cover

Timeline



References

Ahmed, Bayes, Md. Kamruzzaman, Xuan Zhu, Md. Rahman, and Keechoo Choi. 2013. "Simulating Land Cover Changes and Their Impacts on Land Surface Temperature in Dhaka, Bangladesh." *Remote Sensing* 5(11):5969–98. doi: 10.3390/rs5115969.

Chen, Xiao-Ling, Hong-Mei Zhao, Ping-Xiang Li, and Zhi-Yong Yin. 2006. "Remote Sensing Image-Based Analysis of the Relationship between Urban Heat Island and Land Use/Cover Changes." *Remote Sensing of Environment* 104(2):133–46. doi: 10.1016/j.rse.2005.11.016.

Das, Niladri, Prolay Mondal, Subhasish Sutradhar, and Ranajit Ghosh. 2021. "Assessment of Variation of Land Use/Land Cover and Its Impact on Land Surface Temperature of Asansol Subdivision." *The Egyptian Journal of Remote Sensing and Space Science* 24(1):131–49. doi: 10.1016/j.ejrs.2020.05.001.

Grigoraș, Georgiana, and Bogdan Urițescu. 2019. "Land Use/Land Cover Changes Dynamics and Their Effects on Surface Urban Heat Island in Bucharest, Romania." *International Journal of Applied Earth Observation and Geoinformation* 80:115–26. doi: 10.1016/j.jag.2019.03.009.

Huang, Ganlin, and M. L. Cadenasso. 2016. "People, Landscape, and Urban Heat Island: Dynamics among Neighborhood Social Conditions, Land Cover and Surface Temperatures." *Landscape Ecology* 31(10):2507–15. doi: 10.1007/s10980-016-0437-z.

Isaac, Esezi. 2018. "Test for Significance of Pearson's Correlation Coefficient ( )."

Kafy, Abdulla-Al, Milan Saha, Abdullah-Al- Faisal, Zullyadini A. Rahaman, Muhammad Tauhidur Rahman, Desheng Liu, Md. Abdul Fattah, Abdullah Al Rakib, Ahmad E. AlDousari, Sk Nafiz Rahaman, Md Zakaria Hasan, and Md Ahasanul Karim Ahasan. 2022. "Predicting the Impacts of Land Use/Land Cover Changes on Seasonal Urban Thermal Characteristics Using Machine Learning Algorithms." *Building and Environment* 217:109066. doi: 10.1016/j.buildenv.2022.109066.

Kumar, Mithun, Ismail Mondal, and Quoc Bao Pham. 2021. "Monitoring Forest Landcover Changes in the Eastern Sundarban of Bangladesh from 1989 to 2019." *Acta Geophysica* 69(2):561–77. doi: 10.1007/s11600-021-00551-3.

Lemonsu, Aude, Raphaëlle Kounkou-Arnaud, Julien Desplat, Jean-Luc Salagnac, and Valéry Masson. 2013. "Evolution of the Parisian Urban Climate under a Global Changing Climate." *Climatic Change* 116(3):679–92. doi: 10.1007/s10584-012-0521-6.

Li, Xiaoma, Yuyu Zhou, Ghassem R. Asrar, Marc Imhoff, and Xuecao Li. 2017. "The Surface Urban Heat Island Response to Urban Expansion: A Panel Analysis for the Conterminous United States." *Science of The Total Environment* 605–606:426–35. doi: 10.1016/j.scitotenv.2017.06.229.

Lowe, Scott A. 2016. "An Energy and Mortality Impact Assessment of the Urban Heat Island in the US." *Environmental Impact Assessment Review* 56:139–44. doi: 10.1016/j.eiar.2015.10.004.

Mondal, Ismail, Sandeep Thakur, Mukhiddin Juliev, and Tarun Kumar De. 2021. "Comparative Analysis of Forest Canopy Mapping Methods for the Sundarban Biosphere Reserve, West Bengal, India." *Environment, Development and Sustainability* 23(10):15157–82. doi: 10.1007/s10668-021-01291-6.

Morshed, Syed Riad, Md. Abdul Fattah, Md. Nazmul Haque, and Syed Yad Morshed. 2022. "Future Ecosystem Service Value Modeling with Land Cover Dynamics by Using Machine Learning Based Artificial Neural Network Model for Jashore City, Bangladesh." *Physics and Chemistry of the Earth, Parts A/B/C* 126:103021. doi: 10.1016/j.pce.2021.103021.

Steeneveld, Gert-Jan, Jochem O. Klompmaker, Ronald J. A. Groen, and Albert A. M. Holtslag. 2018. "An Urban Climate Assessment and Management Tool for Combined Heat and Air Quality Judgements at Neighbourhood Scales." *Resources, Conservation and Recycling* 132:204–17. doi: 10.1016/j.resconrec.2016.12.002.

Thakur, Sandeep, Debapriya Maity, Ismail Mondal, Ganesh Basumatary, Phani Bhushan Ghosh, Papita Das, and Tarun Kumar De. 2021. "Assessment of Changes in Land Use, Land Cover, and Land Surface Temperature in the Mangrove Forest of Sundarbans, Northeast Coast of India." *Environment, Development and Sustainability* 23(2):1917–43. doi: 10.1007/s10668-020-00656-7.

Thakur, Sandeep, Ismail Mondal, Somnath Bar, Subhanil Nandi, P. B. Ghosh, P. Das, and T. K. De. 2021. "Shoreline Changes and Its Impact on the Mangrove Ecosystems of Some Islands of Indian Sundarbans, North-East Coast of India." *Journal of Cleaner Production* 284:124764. doi: 10.1016/j.jclepro.2020.124764.

Zhang, Fei, Tashpolat Tiyip, Hsiangte Kung, Verner Carl Johnson, Matthew Maimaitiyiming, Mei Zhou, and Juan Wang. 2016. "Dynamics of Land Surface Temperature (LST) in Response to Land Use and Land Cover (LULC) Changes in the Weigan and Kuqa River Oasis, Xinjiang, China." *Arabian Journal of Geosciences* 9(7):499. doi: 10.1007/s12517-016-2521-8.

Zhang, Yili, Jungang Gao, Linshan Liu, Zhaofeng Wang, Minjung Ding, and Xuchao Yang. 2013. "NDVI-Based Vegetation Changes and Their Responses to Climate Change from 1982 to 2011: A Case Study in the Koshi River Basin in the Middle Himalayas." *Global and Planetary Change* 108:139–48. doi: 10.1016/j.gloplacha.2013.06.012.