Correlation Between LST, NDVI and NDBI with Reference to Bengaluru Urban, Karnataka

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ABSTRACT
Urbanization refers to growth in the physical area of the urban settlements as a result of the movement of population from rural to urban areas. Bengaluru is one of the fastest growing metropolitan cities in India, which showed a massive increase in population between 2011 and 2021 (48% increase). This study focuses on the relation of LST with NDVI, NDBI and DEM in Bengaluru urban district using geospatial technologies. The correlation of LST with NDVI, NDBI and DEM were analyzed by using scatter plot. The results were indicating that LST has negative correlation with NDVI (R= -0.38) and positive correlation with NDBI (R = 0.5), whereas with DEM was no relationship even though variation in elevation. NDVI and NDBI relationship was found to be negative (R =-0.21). The findings of the study conclude that urban area has to tackle the negative impacts of temperature due to rapid urbanization and decrease in vegetation or green spaces. Urbanization is inevitable as long as there exists an economic development. Therefore, monitoring of land cover changes would help in better planning for the future. Urban green spaces need to be increased to mitigate the effect of temperature due to urbanization and other factors. Protection of urban water bodies also helps in mitigation. Sustainable development goals which specify on sustainable cities can be implemented with the help of Geospatial technologies to be focused on built-up area and urban planning. Creating awareness at individual level is also a part of mitigation.

Keywords: Climate Change, Heat Island, Urbanisation, Green Cover

Introduction

United Nations (UN) estimation expects urban population to reach 5 billion from the current 3.5 billion by the year 2030. Over 70% of the urban population by the year of 2050 is expected to stay in urban settlements. Urbanization refers to growth in the physical area of the urban settlements as a result of the movement of population from rural to urban areas. India has become one of the world's fastest countries in land cover changes. The conversion of vegetation has made obvious contradiction of water and soil resources supply and demand and flow speeding has enhanced (Pattanayak, 2018). Over the last few decades, a large influx of population that has moved from rural area to urban areas. This influx of population to urban areas has led to clearing of vast areas forest land for urban settlements, result in greenhouse gas emissions (Shreyas, 2020). Urban areas with significant tree cover are up to 5°C cooler compared to open areas and sub-urban areas are 2 to 3 °C lower than areas without trees. Grassy sport fields are 1 to 2°C lower than border areas (Ambinakudige, 2011).

Rise of anthropogenic activities the cropping pattern and vegetation has changed, results in susceptible climatic conditions, change LULC which other way replaces natural vegetation with impervious surfaces like asphalt, concrete and metals. Vegetation indices are analysed to monitor the LULC change (Ghosh *et al.,*2022). Vegetation index varies based on terrain condition and trees cover. Land surface temperature is a parameter which determine the energy exchange between the surfaces of earth and radiant temperature which helps in understanding the change in surface temperature (Anbazhagan and Paramasivan, 2016).
Urban Heat Island is also related to population and the size of the urban area. Heat island developments are also due to the construction of materials of high heat capacity and low solar reflectivity (Ibrahim *et al.,*2016). Urban heat island acts as additional inputs of heat in addition to greenhouse-effect based warming (Kanga *et al*., 2022). LST is an important parameter in agriculture, hydrology, ecology, environment, climate and biogeochemistry (Tan *et al*., 2020). NDVI is reliability determines its robustness of NDVI-related models (Huang *et al.,* 2021). NDBI is linear combination of near infrared band and the middle infrared band used for extraction of urban built-up land (Malik *et al*., 2019). It can be used as an indicator of intensity of development and urban impervious surface (Macarof and Statescu, 2017). Also, the UN sustainable development goal number 11 focuses on making human settlements and cities more sustainable, this requires timely monitoring of urban growth and change in land- use and land-cover (LULC), which is possible with geospatial technology (Shreyas, 2020). Quantitative information of surface temperature across the LULC categories can be obtained by Thermal infrared (TIR) sensors (Yogesh *et al.,* 2009). Analysis of spatial flexibility of the NDVI, LST, NDBaI, and MNDWI are crucial for decision making and natural resources monitoring in natural and environmental investigations (Zareie *et al.,* 2016).

Materials and methods

Study area

Bengaluru is the capital city of the state of Karnataka in the southern part of India. It is known as the 'Silicon Valley of India', it is one of the fastest growing cities in the country and is a hub for technological innovations, start-ups, and information technology (IT) based industries. The city is located at 12°59'N latitude and 77°57'E longitude and has a mean sea elevation of 920 m. The city receives an annual rainfall of around 880 mm. The summer temperature of the city variesfrom18°C to 38°C and the winter temperature varies from12°C to 25°C. The major green spaces like Cubbon park and Lalbagh, along with water bodies like Ulsoor lake, Sankey tank, etc., are home to various flora and fauna in the region. These regions and the green spaces along the periphery of the city harbour a great number of floral and faunal species.

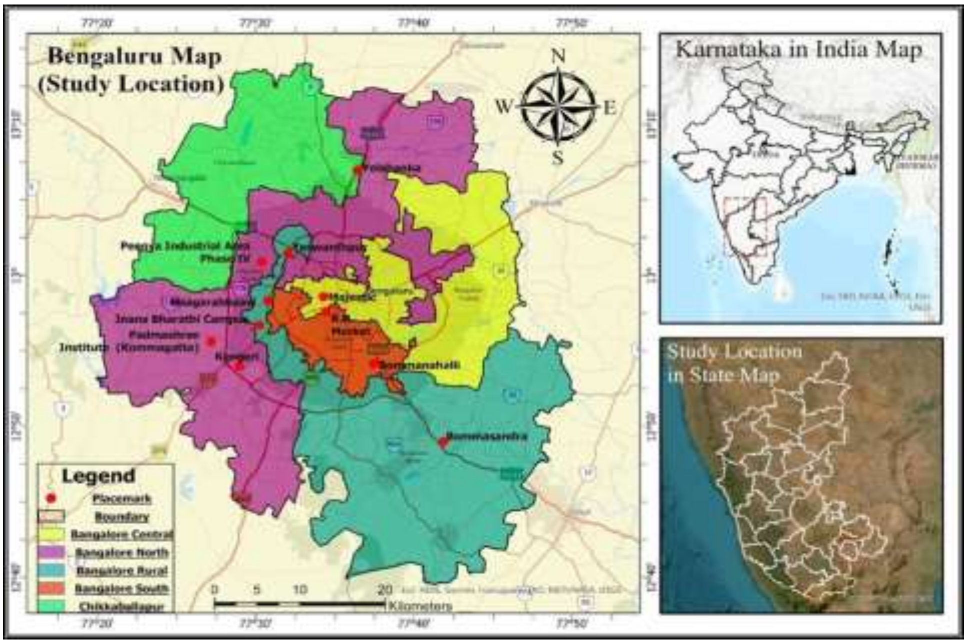

Figure 1: Study area map

Methodology

Data types and sources

Landsat images for two decades were used and The United States Geological Survey USGS (http://earthexplorer.usgs.gov/) provides free downloads of the thermal and multispectral bands of Landsat TM 990, Landsat ETM+ 2013, and Landsat OLI/TIRS 2023. Detailed information regarding these data is presented in Table 1. and QGIS 3.14 version software.

Table1.Details of Remote sensing data for the study.

DATE	Satellite	PATH	ROW
13/04/2013	Landsat8/9 OLI/TIRS	144	51
17/04/2023	Landsat8/9 OLI/TIRS	144	51

Calculation of LST, NDVI, and NDBI

Land Surface Temperature (LST):

The Land Surface Temperature (LST) is the radiative temperature and is calculated using Top of atmosphere brightness temperature, Wavelength of emitted radiance, Land Surface Emissivity.

$$LST = (BT / 1) + W \times (BT / 14380) \times \ln(E)$$

Where:

BT = Top of atmosphere brightness temperature (°C)

W = Wavelength of emitted radiance

E = Land Surface Emissivity

Top of Atmosphere (TOA) Radiance:

Using the radiance rescaling factor, Thermal Infra-Red Digital Numbers can be converted to TOA spectral radiance.

$$L\lambda = ML \times Qcal + AL$$

Where:
Lλ = TOA spectral radiance (Watts/ (m^2 x sr x µm))
ML = Radiance multiplicative Band (No.)
AL = Radiance Add Band (No.)
Qcal = Quantized and calibrated standard product pixel values (DN)

Top of Atmosphere (TOA) Brightness Temperature:
Spectral radiance data can be converted to top of atmosphere brightness temperature using the thermal constant Values in Meta data file.
BT = K2 / ln (k1 / Lλ + 1) - 272.15
Where:
BT = Top of atmosphere brightness temperature (°C)
Lλ = TOA spectral radiance (Watts/ (m^2 x sr x µm))
K1 = K1 Constant Band (No.)
K2 = K2 Constant Band (No.)

NDVI: Normalized difference vegetation index (NDVI)
The Normalized Difference Vegetation Index (NDVI) is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyse remote sensing measurements and assess whether the target being observed contains live green vegetation or not. The NDVI algorithm subtracts the red reflectance values from the near-infrared and divides it by the sum of near-infrared and red bands (Rouse *et al*.,1973).
$NDVI = (BAND5 - BAND4) / (BAND5 + BAND4)$
Whereas Red is (Band 4) with a wavelength of (0.64-0.67 m) and NIR is (Band 5) with a wavelength of (0.85-0.88 m). The range of the NDVI index is from -1 to 1. It typically falls between 0.2 to 0.8 for green plants.
NDBI: The NDBI formula is used to calculate the building density index, is used to determine the density of buildings. Band 5 and Band 6 Landsat 8 imagery is used by NDBI, (Govil *et al.,* 2019)
$NDBI = (BAND\ 6 - BAND5)/(BAND6 + BAND5)$
Where SWIR is Band 6 wavelength of (1.566-1.652) The range of the NDBI value is from -1 to +1. Higher NDBI values indicate built-up regions, whereas lower values indicate water bodies. The vegetation NDBI value is low
DEM: DEM (Digital Elevation Model) data was directly derived from SRTM downloader in QGIS 3.14 software. The download DEM was implemented through preprocessing of extracting by mask tools to delineate and finally the slope map of Bengaluru district was generated.

Results and discussion
Land surface temperature: LST is an important parameter in all physical processes of surface energy and water balance at local and global scales. It plays a key role in inland surface process due to its control of sensible and latent heat flux exchange.

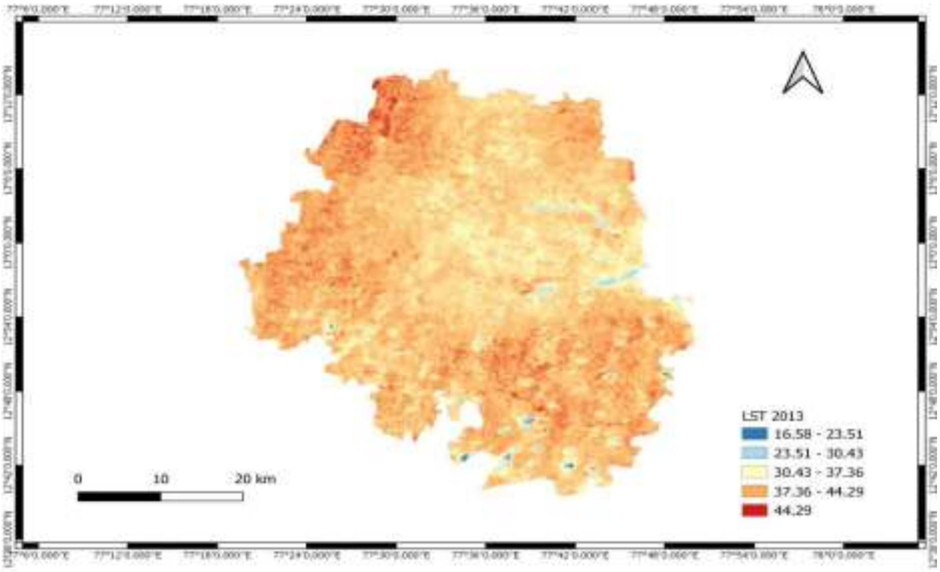

Figure 2: Land surface temperature map during 2013

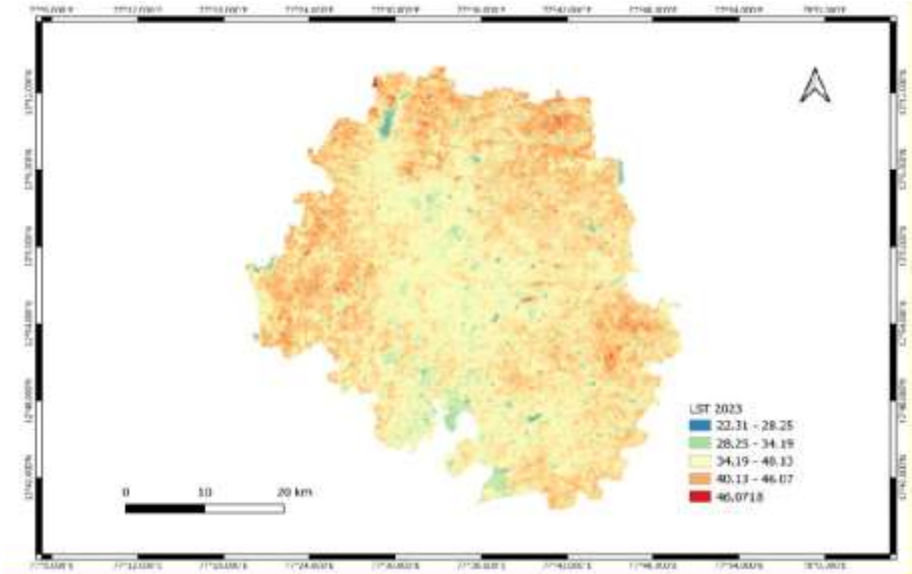

Figure 3: Land surface temperature map during 2023

The minimum LST value in 2013 is16.5°C and maximum value is 44.2°C, with mean value of 35.2°C and standard deviation of 2.56, whereas the minimum LST 22.3°C in 2023 is and maximum LST of 46.0°C, with mean value of 35.8°C with a standard deviation of 2.57. it was observed that the increase of LST from 2013 to 2023 in Bengaluru urban district, some of the regions are influence of various land covers, the growth in population and landuse alteration which change the albedo, thus the minimum LST has increased by 5.73°C and maximum LST has increased by 1.78°C.

Rapid urbanization is also a factor that has an influence on LST data generated that implies the increase in builtup area with the help of NDBI. Therefore, it is important to evaluate LST changes for a comfortable and sustainable city. People's health is also affected due to increase in LST due to heat waves (Jones *et al*., 2022). The increase in land surface temperature is also by urban climate change, Urban Heat Island (UHI), which intensifies due to pollution generated by various human activities. LST increases with human activities as well as impermeable urban areas. Development of green areas can be considered one of the main measures for mitigating increase in LST in urban areas (Garcia *et al.,* 2023).

NDVI: The Normalized Difference Vegetation Index (NDVI) is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyse remote sensing measurements and assess whether the target being observed contains status.

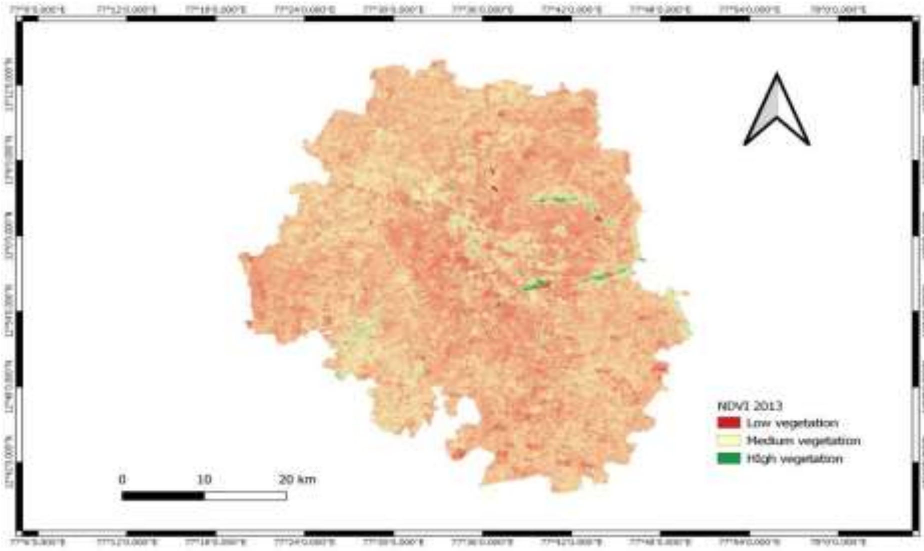

Figure 4: Map showing NDVI values during 2013

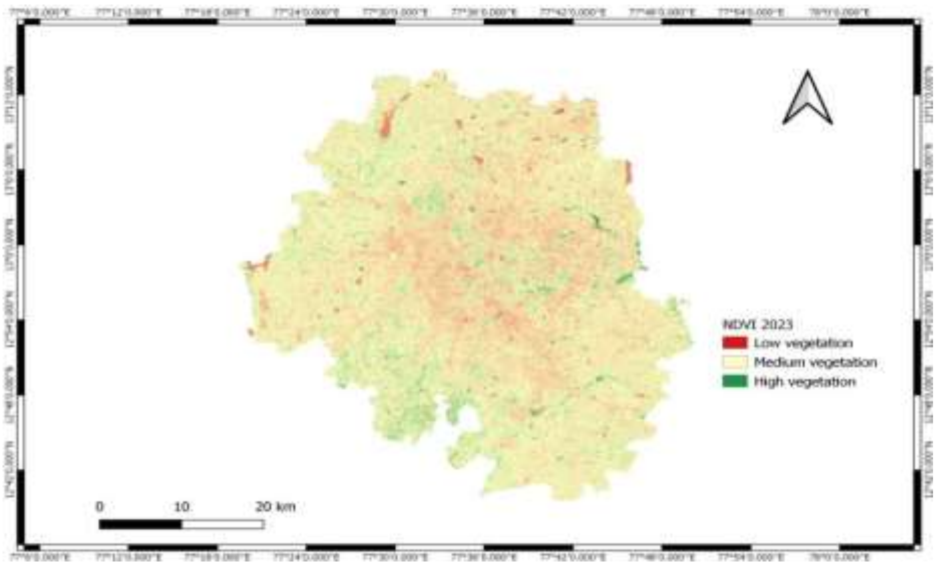

Figure 5: Map showing NDVI values during 2023

The minimum NDVI value in 2013 was -0.05 and maximum value is 0.51, with mean value of 0.14 and standard deviation of 0.14, whereas the minimum NDVI value during 2023 is- 0.16 and maximum value is 0.52, with mean value of 0.17 and standard deviation of 0.175. Urban green spaces, cultivated land and waterbodies are considered to play an important role in variation of LST by providing cooling effect. The maps provide information on low LST values near green spaces and water bodies. The negative correlation between LST and NDVI indicates the same. Vegetation in green spaces produces shade and absorbs the radiation energy by photosynthesis and transpiration, thus cooling down the LST. In contrast to rural areas, urban vegetation experiences richer carbon dioxide concentrations resulting in photosynthetic activity peaking early and higher sensitivity to climate change (Mirsanjari *et al*., 2021). Trees would help to reduce storm water runoff and assist with processing wastewater and minimizing pollution and diseases from sewage water through its use of tree planting. Many cities have established and conserved forests to protect their drinking water resources (Konijnendijk and Randrup, 2004).

NDBI: NDBI is the linear combination of near infrared band and the middle infrared band used for extraction of urban built-up land.

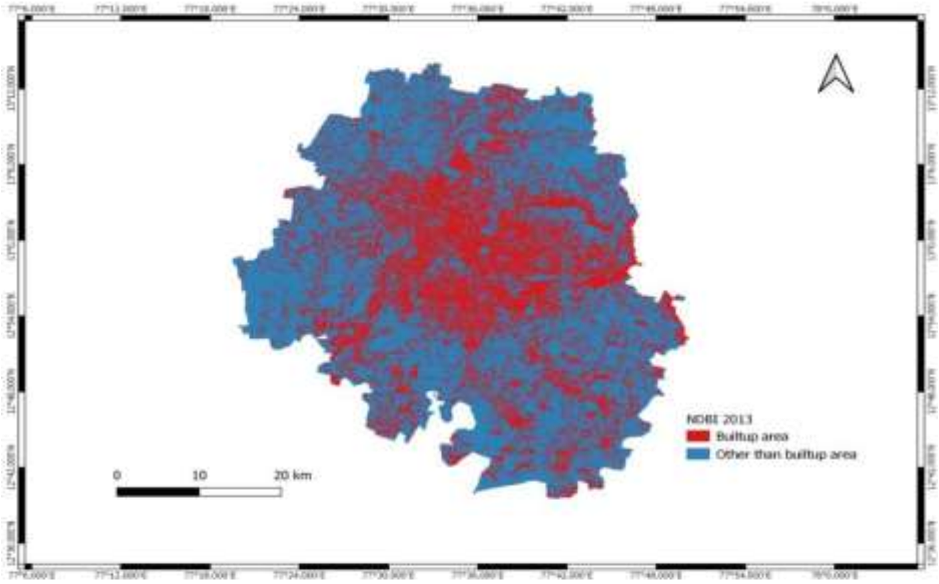

Figure 6: Map showing NDBI values during 2013

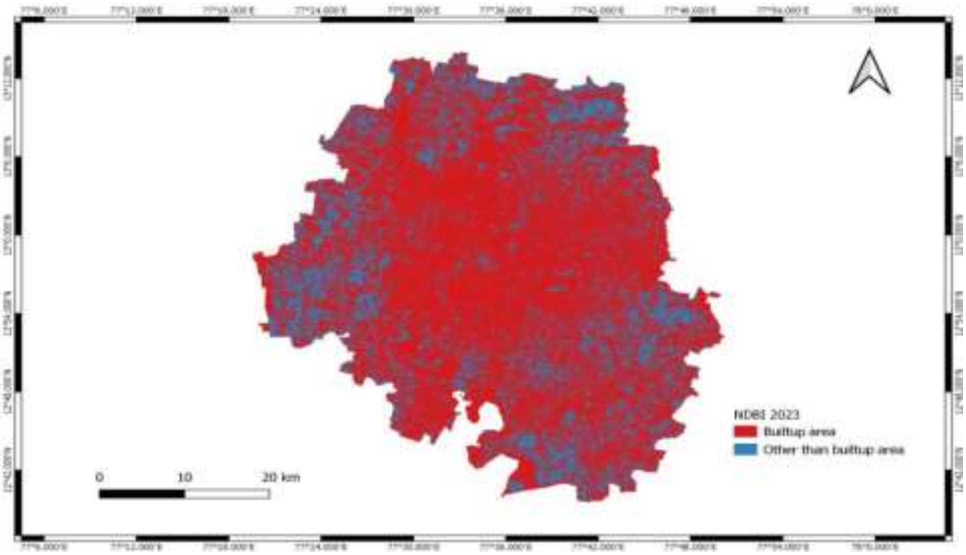

Figure 7: Map showing NDBI values during 2023

The minimum NDBI value in 2013 is 0 and maximum value is 1, with mean value of 0.33 and standard deviation of 0.44. Similarly, the minimum NDVI value in 2023 is 0 and maximum value is 1, with mean value of 0.62 with a standard deviation of 0.48. An significant increase in built up area from 2013 to 2023 in all directions. Economic growth development and population growth drive expansion of built-up areas. This process often led to a reduction of available free space in cities and its surroundings. Urbanization leads to an increased complexicity between land and water development. The augmenting rate of built-up areas in cities leaves less space available for water storage functions. This is a critical situation where it increases the vulnerability for droughts. Urban system offers range of dynamics depending on the consequences being considered. Vegetation follows the seasonal vegetative cycle while being strongly influenced by factors such as the shapes of buildings and specific ecological condition of a given environment (Briottet *et al.,* 2016).

DEM: Digital Elevation Model (DEM) is the digital representation of the land surface elevation with respect to any reference datum.

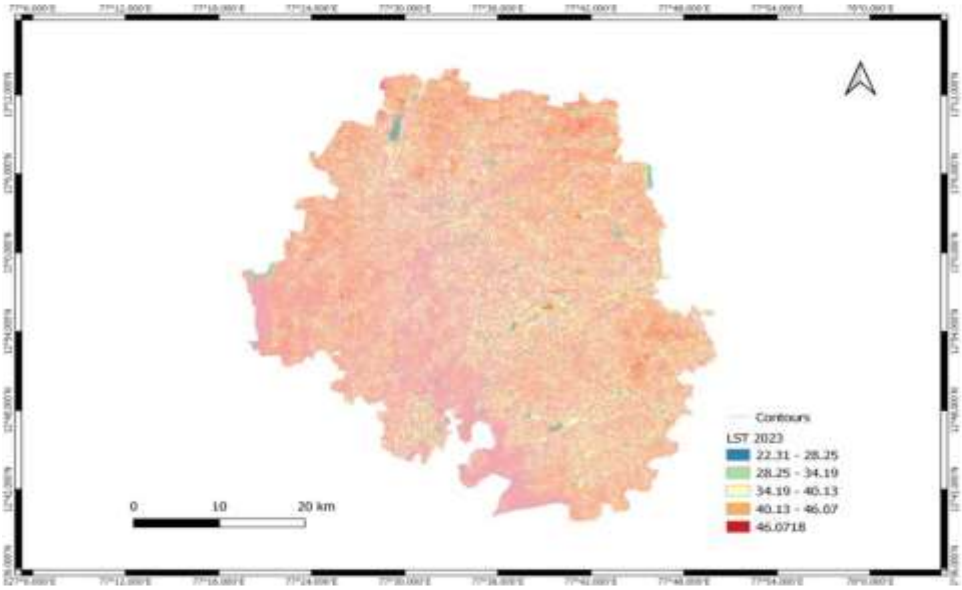

Figure 8: Map showing Land Surface Temperature and Contours

NDVI and NDBI correlated with LST seasonally. Correlation results showed that LST and NDBI had strong positive relationship that is $R^2 = 0.991$ in January,0.981 in May and 0.965 in October, whereas with NDVI it had strong negative correlation withR^2 values 0.993, 0.992, and 0.911 in each season. NDVI and NDBI relationship was also computed which provided results showing strong negative correlation (Malik *et al*., 2019). Although the current studies do not cover the seasonal changes of the parameters the relationship was identified to be the same. Similar studies carried out by (Ahmed *et al*. 2023) shows that LST and elevation correlation was found where R = - 0.51. Zonal analysis of LST for different LULC types showed that built-up and bare soil had the highest mean LST. Bengaluru urban district elevation varies from 720 m to 970 m, but from the maps obtained the LST do not have any correlation with increase or decrease in elevation obtained by DEM data. Tan *et al*., (2020) observed that there was positive correlation when the elevation was 65> m and negative correlation above 300 m due to the presence of water bodies.

Table 2. Statistics of retrieval parameters

Sl.No	Parameters	DATE	Mean	Min	Max	Standard Deviation
1	**LST**	13-04-2013	35.24°C	16.58°C	44.29°C	2.56°C
		17-04-2023	35.83°C	22.31°C	46.07°C	2.57°C
2	**NDVI**	13-04-2013	0.14	-0.05	0.51	0.14
		17-04-2023	0.17	-0.16	0.52	0.17
3	**NDBI**	13-04-2013	0.33	0	1	0.44
		17-04-2023	0.62	0	1	0.48

Correlation between NDVI and LST

The negative correlation between LST and NDVI with R value of - 0.38 (fig 9), indicating the indirect relationship where LST decreases with increase in NDVI. Anbazhagan and Paramasivan (2016) carried out studies between LST and NDVI for almost two decades that is from1992, 2001, and 2010 where it was found out all three had negative correlation where LST increased with decrease in NDVI. The values of co-efficient were - 0.209, - 0.143, and - 0.190 respectively.

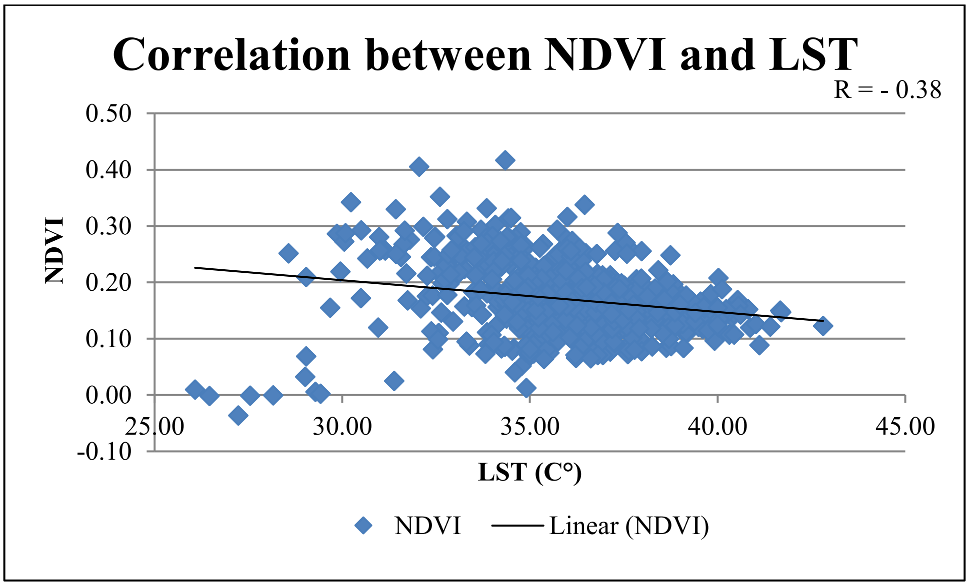

Figure 9: Scatter plot indices correlation between LST and NDVI

Correlation between NDBI and LST

It represents positive correlation between LST and NDBI with R value of 0.5 (Fig 10). This indicates the direct relationship where LST increases with increase in NDBI. The positive correlation between NDBI and LST is another indicator to show that urbanization has an impact on LST, this can lead to urban heat island effect. LST and NDBI had a positive relationship with R^2 values of 0.51, 0.48, and 0.4 and negative relationship with NDVI in the years 1987, 2002, and 2017 respectively (Balew and Korme, 2020).

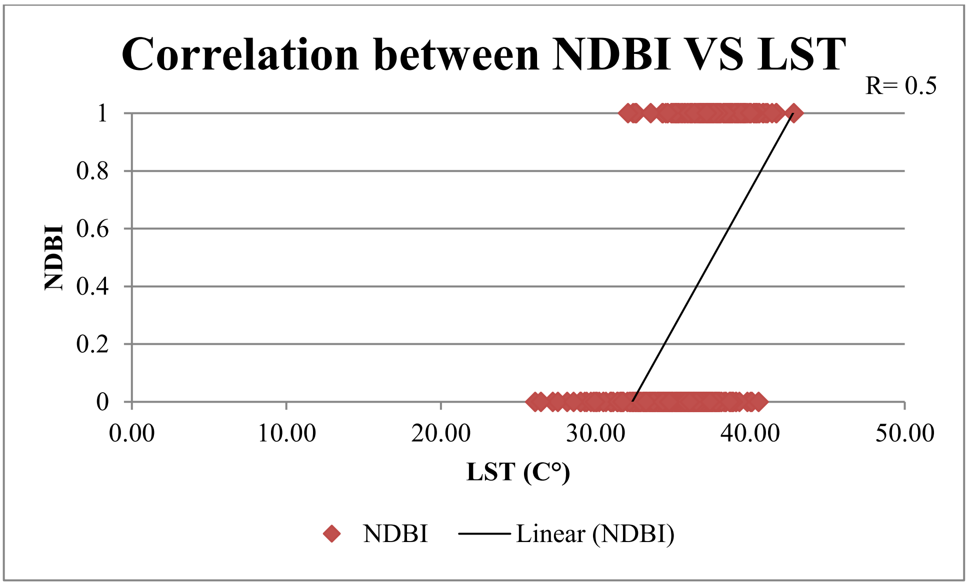

Figure 10: Scatter plot indices correlation between NDBI and LST

Correlation between NDVI and NDBI

The negative correlation between NDBI and NDVI with R value of - 0.21 (Fig 11). This indicates the indirect relationship where NDVI decrease with increase in NDBI. The negative correlation between NDVI and NDBI implies the indirect relationship between NDBI to NDVI. Urban green space helps in carbon storage which fails to do so with decreasing vegetation, hence there is an increase in carbon dioxide and other greenhouse gases.

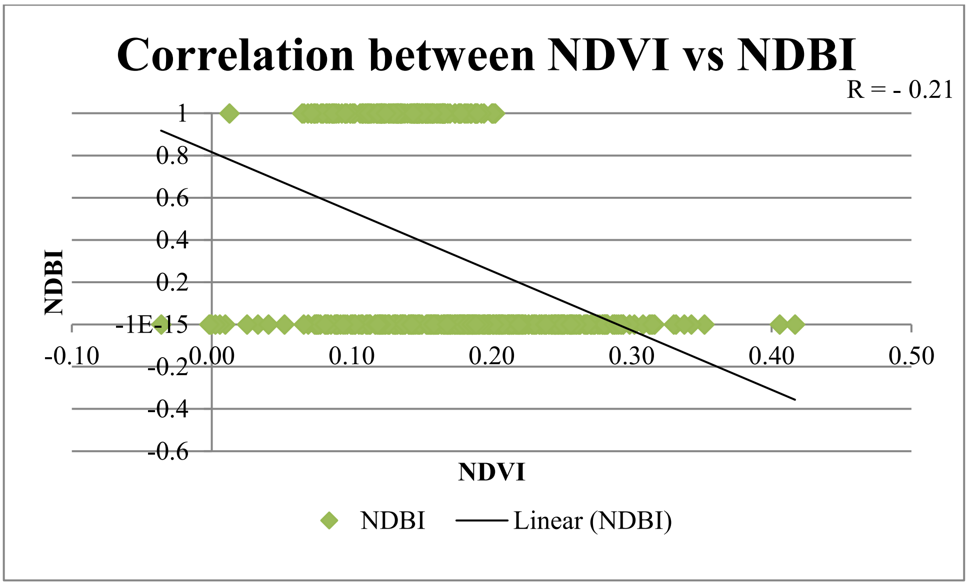

Figure 11: Scatter plot indices correlation between NDVI and NDBI

Decreasing vegetation and built-up areas full of overlapping high buildings in urban areas have reduced solar radiation and carbon dioxide absorption, which poses a risk of increased air temperature. In addition to the increasing number of solar heat-reflecting elements, the heat from human activities also produces greenhouse gases. (Balew and Korme, 2020) carried out studies where LST and NDBI had a positive relationship with R^2 values of 0.51, 0.48, and 0.4 and negative relationship with NDVI during 1987, 2002, and 2017 respectively.

Conclusion

The study has focused on the different aspects that make up an urban area which directly controls the urban climate and has an adverse effect on the population and surrounding environment. The findings of the study conclude that as every year passes by urban area has to tackle the negative impacts of temperature due to rapid urbanization and decrease in vegetation or green spaces. Urbanization is inevitable as long as there exists a need for economic development. Therefore, monitoring the changes would help in better urban planning for the future. Remote sensing comes into major role, which makes easier to monitor in a big way, which is also a cost-effective method. The study suggest that Urban green spaces need to be increased to mitigate the effect of temperature due to urbanization and other factors. Planting of avenue trees is of the initiative taken by the government, which are planted all along the metro line and regular roads with dividers. Protection of urban water bodies also helps in mitigation. Sustainable development goals which specify on sustainable cities can be implemented with the help of Remote Sensing which has to be focused on built-up area, which can be used for urban planning. Creating awareness is also a part of mitigation which can be implemented at individual by voluntarily.

References

1. Ambinakudige, S. (2011). Remote sensing of land cover's effect on surface temperatures: a case study of the urban heat island in Bangalore, India. *Applied GIS*, *7*(1).
2. Anbazhagan, S., & Paramasivam, C. R. (2016). Statistical correlation between land surface temperature (LST) and vegetation index (NDVI) using multi-temporal landsat TM data. *International Journal of Advanced Earth Science and Engineering*,*5*(1), 333- 346.
3. Biryukov, A. D., Olenkov, V. D., & Kolmogorova, A. O. (2021). Urban climate and registration of thermal anomalies of territories using satellite imagery. In *E3S Web of Conferences* (Vol. 266, p. 08008). EDP Sciences.
4. García, D. H., Riza, M., & Díaz, J. A. (2023). Land Surface Temperature Relationship with the Land Use/Land Cover Indices Leading to Thermal Field Variation in the Turkish Republic of Northern Cyprus. *Earth Systems and Environment*, *7*(2), 561-580.
5. Ghosh, S., Kumar, D., & Kumari, R. (2022). Assessing spatiotemporal dynamics of land surface temperature and satellite-derived indices for new town development and suburbanization planning. *Urban Governance*, *2*(1), 144-156.
6. Govil, H., Guha, S., Dey, A. and Gill, N., (2019). Seasonal evaluation of downscaled land surface temperature: A case studyina humid tropical city. Heliyon, *5*(6),
7. Huang, S.,Tang, L.,Hupy,J. P., Wang,Y., & Shao,G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, *32*(1), 1-6.
8. Ibrahim, I., Abu Samah, A., Fauzi, R., & Noor, N. M. (2016). The land surface temperature impact to land cover types. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *41*, 871-876.
9. Kanga, S., Meraj, G., Johnson, B. A., Singh, S. K., PV, M. N., Farooq, M., ...& Sahu, N. (2022). Understanding the Linkage between Urban Growth and Land Surface Temperature—A Case

Study of Bangalore City, India. *Remote Sensing*, *14*(17), 4241.
10. Kant, Y., Bharath, B. D., Mallick, J., Atzberger, C., & Kerle, N. (2009). Satellite-based analysis of the role of land use/land cover and vegetation density on surface temperature regime of Delhi, India. *Journal of the Indian Society of Remote Sensing*, *37*, 201-214.
11. Konijnendijk, C. C., & Randrup, T. B. (2004). Urban forestry. *Encyclopedia of Forest Sciences. Elsevier Science, London*, 471-478.
12. Macarof, P., & Statescu, F. (2017). Comparasion of NDBI and NDVI as indicators of surface urban heat island effect in landsat 8 imagery: a case study of Iasi. *Present Environment and Sustainable Development*, (2), 141-150.
13. Malik, Mohammad Subzar & Shukla, J. & Mishra, S N. (2019). Relationship of LST, NDBI and NDVI using landsat-8 data in Kandaihimmat watershed, Hoshangabad, India. *Indian Journal of Geo-Marine Sciences*. 48. 25-31.
14. Mirsanjari, M. M., Mohammadyari, F., Visockiene, J. S., & Zarandian, A. (2021). Relationship between land surface temperature and urbanization in Vilnius district. *Environmental Monitoring and Assessment*, *193*, 1-14.
15. Pattanayak, S. P., & Diwakar, S. K. (2018). Seasonal comparative study of NDVI, NDBI and NDWI of Hyderabad City (Telangana) based on LISS-III image using remote sensing and DIP. *Khoj: An International Peer Reviewed Journal of Geography*, *5*(1), 78-86.
16. Rouse Jr, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973, December). Paper a 20. In *Third earth resources technology satellite-1 symposium: The proceedings of a symposium held by Goddard space flight center at Washington, DC on* (Vol. 351, p. 309).
17. Tan, J., Yu, D., Li, Q., Tan, X.,& Zhou, W. (2020). Spatial relationship between land- use/land-cover change and land surface temperature in the Dongting Lake area, China. *Scientific Reports*, *10*(1), 9245.
18. Tan, K. C., Lim, H. S., MatJafri, M. Z., & Abdullah, K. (2010). Landsat data to evaluate urban expansion and determine land use/land cover changes in Penang Island, Malaysia. *Environmental Earth Sciences*, *60*(7), 1509-1521.