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Assessing the intensity of land surface temperature in Thiruvarur district (India).

Evaluación de la intensidad de la temperatura de la superficie terrestre en el distrito de Thiruvarur (India).

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ABSTRACT

Nature gives way to the emergence of concrete jungles as cities grow around them. The majority of these concrete masses are highly reflective, changing the surrounding temperature. Hence, urbanized regions often have higher average temperatures than their surrounding rural areas. This phenomenon is termed Urban Heat Island (UHI). The intensity of UHI depends up on Land Surface Temperature (LST). This paper intends to study the intensity of LST in the Thiruvarur district and its correlation with Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) using Landsat 8 Imageries (OLI & TIRS) of January 2018. To calculate the LST, we used the mono-window algorithm. The result shows that LST intensity varies from 20.68°C to 32.3°C, with the maximum being in built-up areas and the minimum being in vegetation areas and water bodies. The Pearson regression shows that there is a negative correlation ($r = -0.925$, $P < 0.5$) between LST & NDVI and a positive correlation ($r = 0.925$, $P < 0.5$) between LST and NDBI. The strong positive correlation of NDBI confirms the influence of urbanization on Surface Urban Heat Island (SUHI). The negative correlation between LST and NDVI shows that green covers can mitigate it. Hence, this study conclusively demonstrates that urbanization can raise temperatures, showing that sustainable development in cities is essential for sustainable growth.

Keywords: Landsat, NDVI, NDBI, LST, Tamil Nadu, India.

RESUMEN

La naturaleza da paso a la aparición de junglas de hormigón a medida que las ciudades crecen a su alrededor. La mayoría de estas masas de hormigón son altamente reflectantes, cambiando la temperatura ambiente. Por lo tanto, las regiones urbanizadas a menudo tienen temperaturas promedio más altas que las áreas rurales circundantes. Este fenómeno se denomina Isla de Calor Urbano (UHI). La intensidad de UHI depende de la temperatura de la superficie terrestre (LST). Este artículo tiene la intención de estudiar la intensidad de LST en el distrito de Thiruvarur y su correlación con el Índice de vegetación de diferencia normalizada (NDVI) y el Índice de construcción de diferencia normalizada (NDBI) utilizando imágenes Landsat 8 (OLI y TIRS) de enero de 2018. Para calcular el LST, usamos el algoritmo mono-ventana. El resultado muestra que la intensidad de LST varía de 20.68°C a 32.3°C, siendo el máximo en áreas edificadas y el mínimo en áreas de vegetación y cuerpos de agua. La regresión de Pearson muestra que existe una correlación negativa ($r = -0{,}925$, $P < 0{,}5$) entre LST y NDVI y una correlación positiva ($r = 0{,}925$, $P < 0{,}5$) entre LST y NDBI. La fuerte correlación positiva de NDBI confirma la influencia de la urbanización en la isla de calor urbana superficial (SUHI). La correlación negativa entre LST y NDVI muestra que las cubiertas verdes pueden mitigarla. Por lo tanto, este estudio

demuestra de manera concluyente que la urbanización puede elevar las temperaturas, lo que demuestra que el desarrollo sostenible en las ciudades es esencial para el crecimiento sostenible.
Palabras clave: Landsat, NDVI, NDBI, LST, Tamil Nadu, India.

INTRODUCTION

The increasing demands and desires of human societies have led to the evolution and transformation of settlements into villages and cities. Urban areas are growing faster than ever before. With a general lack of vegetation, they are notable for their concrete jungle appearance with large brick and concrete towers over the horizons (Chandramathy, 2018).

The global average temperature has increased immensely since the 19th century, and as a result of industrialization and rapid development, significant urban areas have been emerged (Bica Grondona et al., 2013). Currently, over half the World's population lives in cities (Cohen, 2003). Compared to the developed countries in North America and Europe, the people living in urban settlements are smaller in Asia. However, rapid urbanization is currently undergoing in the Asian region, and its population in urban areas are supposed to increase by 64 percent by 2025 (UN, 2014, 2016).

Urbanization improves the quality of life and economic growth in fast-developing countries. On the other hand, urban growth without proper planning profoundly impacts the environment (Ranagalage et al., 2017). The adverse effects of urbanization and urban sprawl on the environment include loss of vegetation, micro-organisms, water bodies, increase in pollution and greenhouse gaseous, the formation of Urban Heat Islands (UHIs), biodiversity degradation, and spread of diseases (Estoque and Murayama, 2014; Son and Thanh, 2018). The most visible effects of rapid urbanization are the loss of vegetation cover and increased concrete infrastructures (Carlson and Traci Arthur, 2000; Du et al., 2010). These are the main factors that can increase the Land Surface Temperature (LST), an indicator for measuring UHIs. UHI can be defined as the appearance of higher atmospheric and land surface temperatures in urban areas compared to the surrounding rural areas (Voogt and Oke, 2003). According to the United States Environmental Protection Agency (EPA), the annual mean air temperature of a city with one million people or more can be 1.8 to 5.4 degrees Fahrenheit (1–3°C) warmer than surrounding areas. In the evening, the difference can be as high as 22°F (12°C). Two types of UHIs observed are: Surface Urban Heat Island (SUHI), which is observed based on land surface temperature (LST), which is the skin temperature of the land surface, and the other one is atmospheric urban heat island (AUHI), which is usually measured based on the air temperature (Singh and Grover, 2014; Jeevalakshmi et al., 2017; Ranagalage et al., 2017). The studies done on LST & UHIs will help urban planners and policymakers to make the cities more sustainable. In China, extensive studies have been conducted on LST & UHIs, e.g., Li & Liu (Li and Liu, 2008) analyzed the relationship between LST, NDVI & NDBI. Significant studies in India are done on the Megacities like Delhi, Mumbai, etc. The UHI and NDVI of Delhi and Mumbai were analyzed by Grover and Singh (Grover and Singh, 2015), and Javed Mallick and B.D Bharath (Javed Mallick and B.D.Bharath, 2008) estimated the LST of Delhi. In Tamil Nadu, the majority of studies are of Chennai. The LST and LULC of Chennai were examined by Devadas and Amirtham (Amirtham and Devadas, 2009). So far, no research has been done on Thiruvarur. Even though Thiruvarur is not a well-urbanized area, it is an emerging one after Central University's construction. Hence, this study should therefore be integrated into urban planning and policymaking in the Thiruvarur district for a sustainable future.

MATERIAL AND METHODS

Most UHI studies are focused on summer season as it is when temperature peaks are observed (Yuan and Bauer, 2007; Li and Liu, 2008; Johnson et al., 2009; Singh and Grover, 2014). But in the case of Thiruvarur, there are vast agricultural areas that shows higher LST, which will make it difficult to differentiate it from urban areas. In winters, it can be distinguished easily as the agricultural lands have lesser LST. Numerous studies are done in the winter season for better results depending upon the study area's favourable conditions (Ranagalage et al., 2017; Veettil and Grondona, 2018). In this paper, the LST of Thiruvarur district is derived from Landsat 8 imageries using the mono-window (MW) algorithm in ArcGIS 10.2.1 software. Band 10 data of Landsat 8 (Table 1) is used as a single spectral band for LST estimation because calibration notifications issued by the United States Geological Survey (USGS) indicate that the data from the Landsat 8 thermal infrared sensor (TIRS) Band 11 shows large uncertainty (Rongali et al., 2018). Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) are also calculated for images and correlated with the LST. NDVI values indicate the degree of vegetation greenness (Lo and Quattrochi, 2003), while NDBI shows the intensity of built-up areas and impervious areas (Zha et al., 2003). The multispectral remote sensing images of the Thiruvarur region were downloaded from the USGS website (https://www.usgs.gov/). Satellite data over the Thiruvarur region (WRS Path 142 & Row 53) of 7th January 2018 has been used in this study. The satellite image has a 0.36 cloud cover. The images were resampled using the nearest neighbour method. All the data are re-projected to a Universal Transverse Mercator (UTM) coordinate system, datum WGS84, zone 44.

NDVI, NDBI, Vegetation proportion calculation, emissivity calculation, LST calculation, etc., were performed using the ArcGIS 10.2.1 software platform. A detailed portrayal of the methodology is outlined below (Figure 1).

Conversion to TOA Radiance: TIRS band data can be converted to TOA spectral radiance using the radiance rescaling factors provided in the metadata file (Qin et al., 2001; Rongali et al., 2018).

$$L\lambda = M_L Q_{cal} + A_L \tag{1}$$

Where, $L\lambda$ = TOA spectral radiance (Watts/(m2*srad*μm)), M_L = Band-specific multiplicative rescaling factor from the metadata (RADIANCE_MULT_BAND_x, where x is the band number), A_L = Band-specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_x, where x is the band number), Q_{cal} = Quantized and calibrated standard product pixel values (DN).

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Table 1. Band Designations of Landsat 8

Band Designations	Wavelength (µm)	Resolution (m)
Band 1 (Coastal Aerosol)	0.43 - 0.45	30
Band 2 (Blue)	0.45 - 0.51	30
Band 3 (Green)	0.53 - 0.59	30
Band 4 (Red)	0.64 - 0.67	30
Band 5 (Near Infrared)	0.85 - 0.88	30
Band 6 (Short wave infrared)	1.57 - 1.65	30
Band 7 (Short wave infrared)	2.11 - 2.29	30
Band 8 (Panchromatic)	0.50 - 0.68	15
Band 9 (Cirrus)	1.36 - 1.39	30
Band 10 (Thermal infrared)	10.6 - 11.19	100
Band 11 (Thermal infrared)	11.50 - 12.51	100

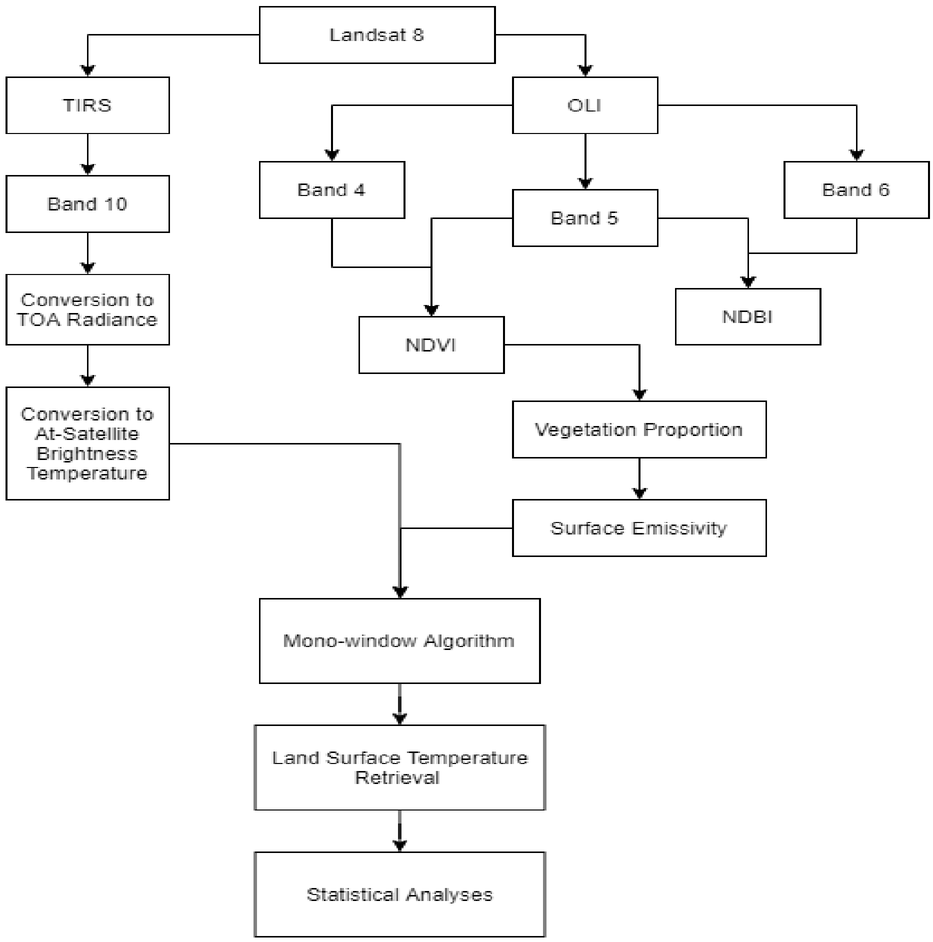

Figure 1. Flow chart of Methodology

Conversion to At-Satellite Brightness Temperature: TIRS band data can be converted from spectral radiance to brightness temperature using the thermal constants provided in the metadata file (Wang et al., 2015; Jeevalakshmi et al., 2017).

$$BT = \frac{K_2}{\ln\left[\left(\frac{K_1}{L\lambda}\right)+1\right]} - 273.15 \tag{2}$$

Where, T = At-satellite brightness temperature (K), $L\lambda$ = TOA spectral radiance [Watts/(m2*srad*μm)], K_1 = Band-specific thermal conversion constant from the metadata (K1_CONSTANT_BAND_x, where x is the band number, 10 or 11), K_2 = Band-specific thermal conversion constant from the metadata (K2_CONSTANT_BAND_x, where x is the band number, 10 or 11)

Land Surface Temperature (LST) Retrieval: Firstly, land surface emissivity is calculated using the Equation given below (Sobrino et al., 2004).

$$\varepsilon = 0.004P_v + 0.986 \tag{3}$$

Where, ε = Emissivity, P_v = Proportion of vegetation which is extracted from the NDVI value (Ranagalage et al., 2017).

$$P_v = \left[\left(NDVI - NDVI_{\min} / NDVI_{\max} - NDVI_{\min}\right)\right]^2 \tag{4}$$

Where, NDVI is the normalized difference vegetation index derived in Equation (6). The $NDVI_{\min}$ and $NDVI_{\max}$ are the minimum and maximum values of the NDVI, respectively.

The emissivity-corrected LST values in Degree Celsius were then retrieved using given Equation (Qin et al., 2001; Jeevalakshmi et al., 2017; Ranagalage et al., 2017; Rongali et al., 2018).

$$LST\left(°C\right) = BT/1 + \left(\lambda \times BT/\rho\right)\ln\varepsilon \tag{5}$$

Where, BT = Landsat 8 Band 10 at-satellite brightness temperature; λ = wavelength of emitted radiance (λ = 10.8 μm for Landsat TIRS Band 10); ρ = h × c/σ (1.438 × 10 − 2 mK), σ = Boltzmann constant (1.38 × 10 − 23 J/K), h = Planck's constant (6.626 × 10 − 34 Js), c = velocity of light (2.998 × 108 m/s); ε is the land surface emissivity.

Calculation of NDVI and NDBI: The NDVI is a significant indicator of urban climate. The NDVI values range from −1 to 1, with positive values representing vegetated areas and negative values representing non-vegetated areas (Zhang et al., 2009). NDVI can be calculated in ArcGIS by applying the given formula (Ranagalage et al., 2017).

$$NDVI = \left(NIR - RED\right)/\left(NIR + RED\right) \tag{6}$$

Where, NIR = band 5 (for Landsat OLI—wavelength 0.85–0.88 μm) and RED = band 4 (for Landsat OLI—wavelength 0.64–0.67 μm).

The NDBI, on the other hand, is an index for identifying and classifying built-up areas or impervious surfaces. The positive values of the NDBI indicate built-up areas, and those close to 0 indicate vegetation, while the negative values mostly represent water bodies. The NDBI is derived by the Equation given below (Zha et al., 2003).

$$NDBI = (MIR - NIR)/(MIR + NIR) \tag{7}$$

Where, MIR = band 6 (for Landsat 8—wavelength 1.57–1.65 μm) and NIR = band 5 (for Landsat OLI—wavelength 0.85–0.88 μm).

Statistical Analysis: Using IBM SPSS Statistics 20, scatter plots were created, and a Pearson correlation was used to determine the correlation of LST with NDVI and NDBI (Yue et al., 2007; Gurjar, 2015).

RESULTS AND DISCUSSION

Spatial distribution of LST; The spatial distribution of LST, NDVI, and NDBI of Thiruvarur district in 2018 are analyzed to understand the intensity and pattern of SUHI (Figure 2). On 7th January 2018 (04:59:25 GMT), the LST in Thiruvarur district ranged from 20.68◦C – 32.30◦C, with a mean temperature of 25.44◦C and standard deviation of 3.28 (Table 2).

Table 2. Descriptive Statistics of the Retrieved NDVI, NDBI & LST

Indicator	Minimum	Maximum	Mean	Standard Deviation
NDVI	-0.16	0.49	0.17	0.2
NDBI	-0.51	0.22	-0.13	0.19
LST	20.68	32.3	25.44	3.28

It is seen that high LST values are found mostly along the coastal belt (29◦C - 32◦C), urban areas (27◦C - 30◦C), and barren lands (28◦C - 31◦C), while vegetation cover (22◦C) and water bodies (21◦C) had low LST. Mannargudi taluk has the highest LST area at the taluk level, ranging between 32◦C and 22◦C. It is noted that impermeable urban regions correspond to higher LST in all Taluks, including Thiruvarur (28◦C), Thiruthuraipoondi (28◦C), Needamangalam (30◦C), Kodavasal (27◦C) and Nannilam (27◦C), Peralam (27◦C), Valangaiman (28◦C), Koradacheri (27◦C), Muthupet (27◦C), Kuthanallur (27◦C). On the other hand, lower LST was recorded for the surrounding rural areas (22◦C-25◦C). In Mannargudi, the LST of rural areas is 22◦C, and 23◦C in Thiruvarur. The LST dips to 22◦C at Valangaiman Taluk and Kodavasal Taluk, located north-western part of the district with the lowest urban population of 11.7% and 10.4%, respectively (Census of India, 2011).

Not all cities have the same LST pattern (Figure 2a & 2b). Urban areas like Thiruvarur, Needamangalam, Thiruthuraipoondi, Kodavasal has radial pattern while Kuthanallur, Koradacheri, and Valangaiman has a linear pattern. In Mannargudi, it is scattered because of the presence of large areas of barren lands.

Spatial distribution of NDVI and NDBI: The NDVI values in the district ranged from -0.16 to 0.49, with a mean of 0.17. Areas with high NDVI values were located mostly in the north-western parts of the district, corresponding to Valangaiman (0.47), Kodavasal (0.47), and Needamangalam (0.48) Taluks (Figure 2c). The lowest NDVI values are seen at the district's eastern and southern parts, corresponding to Mannargudi (-0.14) and Thiruthuraipoondi (-0.16) Taluks. Urban centers have comparatively lower NDVI values (0.13-0.16) than their surrounding rural areas (0.32-0.39) as the cities convert their green cover to concrete structures.

The NDBI values ranged from -0.51 to 0.22, with a mean of -0.13. Areas with high NDBI values were concentrated mostly near the urban centers (0.04-0.14), along the roads (0.01-0.00), and coastal belt (0.07-0.09) (Figure 2d). Lower NDBI values are mostly seen around the rural areas [-0.27-(-0.28)].

Inter-linkages between LST, NDBI, and NDVI in Thiruvarur district: Most of the Taluks that have higher LST have lower NDVI and Higher NDBI and vice versa. E.g., LST in Valangaiman taluk ranges from 28◦C-22◦C, and a larger part of the taluk has less LST as it is being covered by vegetation. It has the highest mean NDVI (0.33) and lowest mean NDBI (-0.22). Urban areas like Thiruvarur, Needamangalam, and Mannargudi has Higher LST and NDBI (Table 3).

The scatterplots graph between the NDVI and LST (Figure 3) and Pearson correlation coefficient reveals that LST is negatively correlated with NDVI across all the points. Pearson correlation ($r = -.953$, $P < 0.05$) (Table 4) shows that there is a strong negative correlation between LST and NDVI. So, it is evident that healthy vegetation covers can reduce the LST and hence the intensity of SUHI.

The spatial pattern of NDBI is considerably similar to the spatial pattern of LST (Figure 2), indicating a positive linear relationship between them. The scatter plot graph (Figure 4) and Pearson correlation coefficient ($r = 0.988$, $P < 0.05$) (Table 5) for LST and NDBI confirms the strong positive correlation between LST and NDBI. It shows that the intensity of built-up areas directly influences the LST and SUHI phenomena.

As it is clear that NDVI and NDBI show how built-up areas elevate the LST and how green covers can mitigate them. Hence, they have a crucial role in urban planning and policymaking.

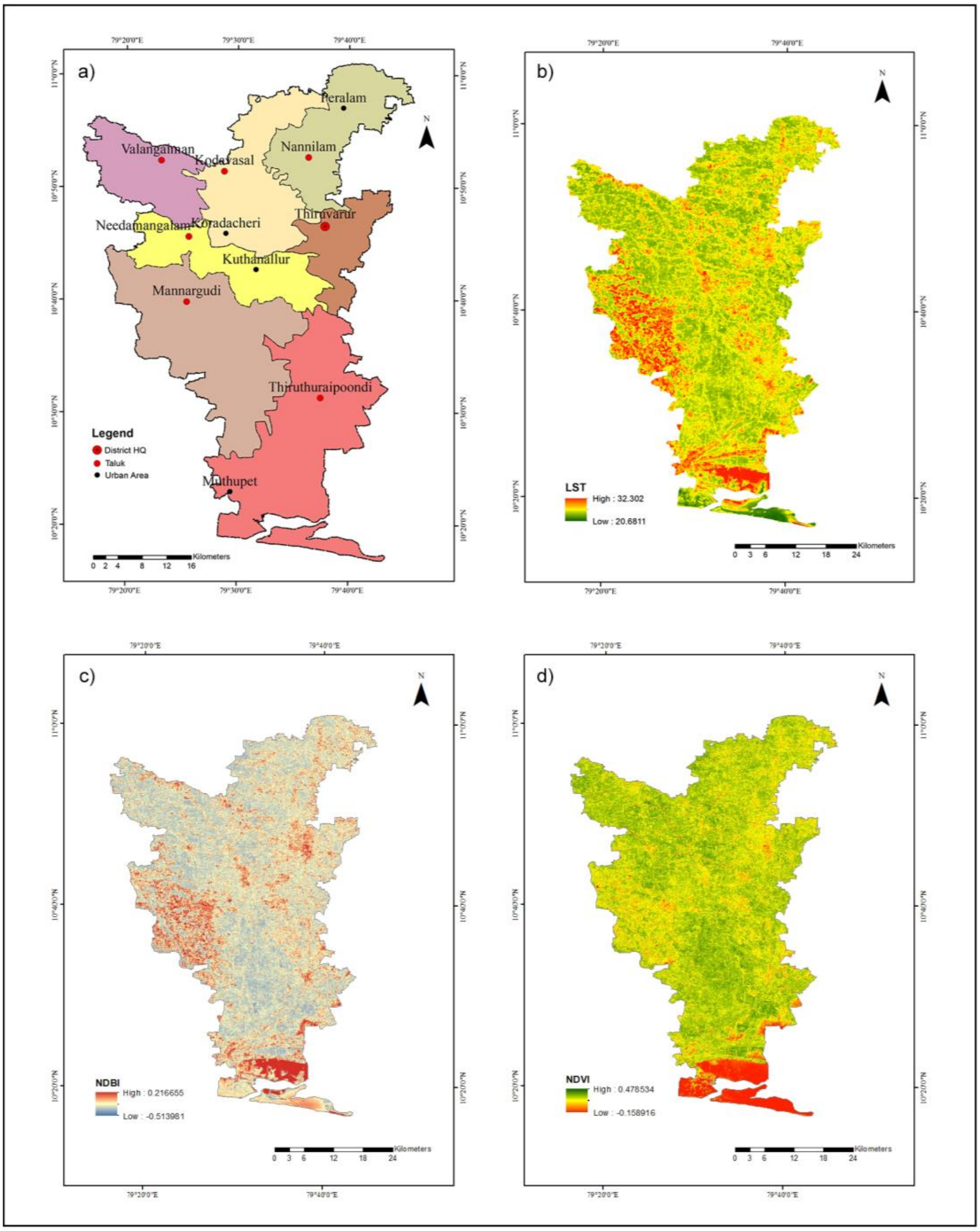

Figure 2. a) Administrative Map of Thiruvarur District, b) Land Surface Temperature Map of Thiruvarur District, c) Normalized Difference Vegetation Index Map of Thiruvarur District, d) Normalized Built-up Index Map of Thiruvarur District

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Table 3. Taluk Wise Descriptive Statistics of LST, NDVI & NDBI

Taluks	LST(°C)	MEAN	NDVI	MEAN	NDBI	MEAN
Kodavasal	27-22	23	-0.01 - 0.46	0.32	-0.35 - 0.08	-0.21
Mannargudi	32-22	24	-0.14 - 0.47	0.31	-0.51 - 0.14	-0.19
Nannilam	27-22	23	-0.05 - 0.46	0.3	-0.34 - 0.1	-0.2
Needamangalam	30-22	24	-0.03 - 0.48	0.31	-0.35 - 0.13	-0.2
Thiruthuraipoondi	32-21	24	-0.16 - 0.47	0.24	-0.39 - 0.2	-0.18
Thiruvarur	28-22	23	-0.07 - 0.47	0.31	-0.34- 0.22	-0.19
Valangaiman	28-22	23	-0.02 - 0.47	0.33	-0.36 - 0.08	-0.22

Table 4. Pearson correlation between LST and NDVI

		NDVI	LST
NDVI	Pearson Correlation	1	-.953**
	Sig. (2-tailed)		.000
	N	100	100
LST	Pearson Correlation	-.953**	1
	Sig. (2-tailed)	.000	
	N	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5. Pearson correlation between LST and NDBI

		NDBI	LST
NDBI	Pearson Correlation	1	.988**
	Sig. (2-tailed)		.000
	N	100	100
LST	Pearson Correlation	.988**	1
	Sig. (2-tailed)	.000	
	N	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

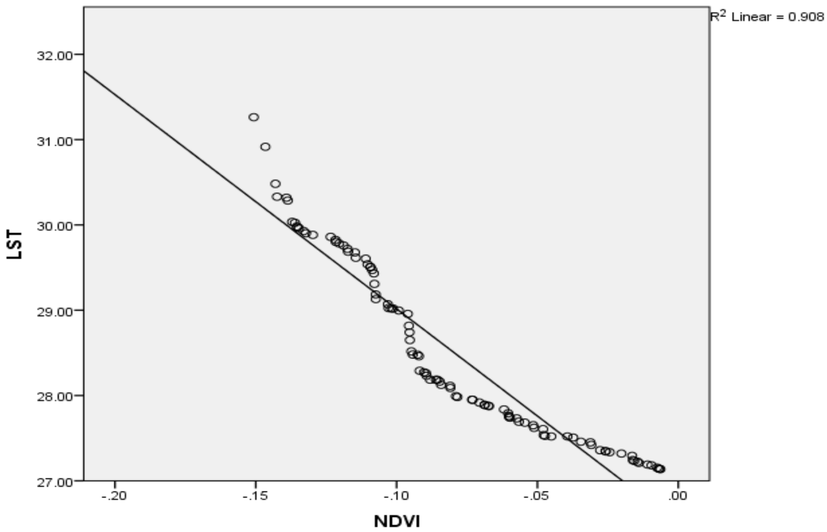

Figure 3. Scatter Plots Between LST and NDVI

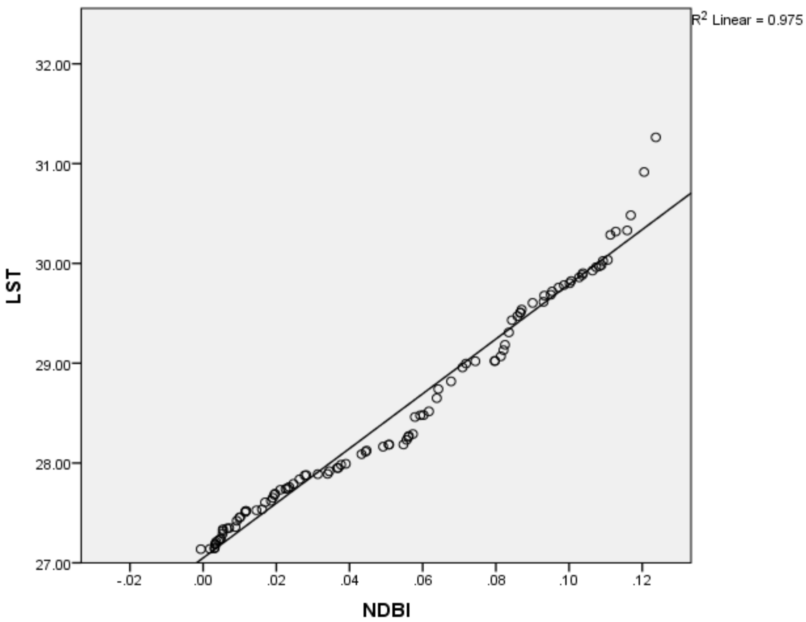

Figure 4. Scatter Plots Between LST and NDBI

As conclusion and recommendations, in this study, the spatial patterns of LST in the Thiruvarur district in the context of the SUHI phenomenon using Landsat 8 data were analyzed. It was found that the intensity of LST in urban areas (Around 27◦C) and barren lands (Around 31◦C) is high compared to the surrounding vegetation areas (22◦C). The significant, strong positive correlations between LST and NDBI confirm the strong influence of urbanization on the formation of SUHI in the Thiruvarur district. Negative correlations between LST and NDVI reflect that green cover can mitigate UHI. The LST, NDVI, and NDBI research studies are essential to city and town planners and government officials who want to see a more holistic understanding of the urban environment for sustainable developments. This paper shows the need for urban greening and water resources preservation to mitigate warming effects due to SUHI, as this land covers act as heat moderators.

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