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Urban Heat Island Dynamics in Johor Bahru, Malaysia: Influence of Vegetation and Urbanisation on Surface Temperature

Mohd Radhie Mohd Salleh[1*], Radzuan Sa'ari[1], Mohamad Hidayat Jamal[1], Nor Eliza Alias[1], Muhammad Zulkarnain Abdul Rahman[2], Noraliani Alias[1], Ahmad Razali Yusoff[3], Shamila Azman[1], Erwan Hafizi Kasiman[1]

[1]Department of Water and Environmental Engineering, Faculty of Civil Engineering, Universiti Teknologi Malaysia, Johor Bahru, Johor, MALAYSIA
[2]Department of Geoinformation, Faculty of Built Environment and Surveying, Universiti Teknologi Malaysia, Johor Bahru, Johor, MALAYSIA
[3]Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia, Johor Bahru, Johor, MALAYSIA

*Corresponding author: mohdradhie@utm.my

***Abstract* –** Urban heat islands (UHIs) pose escalating challenges for tropical cities, intensifying thermal discomfort and exacerbating energy demands. This study examines the impact of vegetation cover and built-up intensity on land surface temperature (LST) in Johor Bahru, Malaysia, by combining remote sensing-derived indices, including the normalised difference vegetation index (NDVI) and the normalised difference built-up index (NDBI), with multiple regression modelling and spatial mapping. Landsat 8 imagery was processed to generate LST, NDVI, and NDBI layers, revealing heterogeneous spatial distributions characterised by pronounced thermal hotspots in densely built-up zones and cooler surfaces in areas of higher vegetation density. Unlike most prior NDVI–NDBI–LST studies that treat these indices separately, this study explicitly quantifies both their individual effects and their interaction. Simple linear regressions showed a moderate inverse relationship between NDVI and LST (adjusted $R^2 = 0.253$) and a positive association between NDBI and LST (adjusted $R^2 = 0.568$). Incorporating both indices into a multiple regression model explained approximately 57% of the variability in LST, with NDBI emerging as the dominant predictor. Introducing an interaction term (NDVI × NDBI) further improved model performance (adjusted $R^2 = 0.579$), highlighting that the cooling effect of vegetation is contingent upon surrounding built-up intensity. Spatial mapping underscored these findings, visually delineating areas where vegetation most effectively mitigates surface warming and identifying transitional zones that could benefit from targeted greening interventions. The results highlight the combined impact of vegetation and impervious surfaces on shaping urban thermal environments, providing critical insights for developing nuanced, context-specific urban heat mitigation strategies.

Keywords – *Urban Heat Island, GIS, Remote Sensing*

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1.0 Introduction

Urban heat islands (UHIs) have emerged as a critical environmental concern due to their adverse impacts on urban ecological conditions and the overall livability of cities, especially in rapidly expanding tropical megacities (Estoque, Murayama, & Myint, 2017; Rizwan & Dennis, 2008). Characterised by elevated land surface temperatures (LST) within urbanised areas relative to surrounding rural regions, UHI phenomena exacerbate energy demands, impair human thermal comfort, and increase vulnerability to heat-related illnesses (Li, Zhou, Asrar, Imhoff, & Li, 2017; Santamouris, 2015). In Southeast Asia, the pace of urban expansion has been accompanied by significant transformations in land use, often involving the replacement of vegetated areas with impervious surfaces (Estoque et al., 2017). Despite this, comprehensive spatial analyses quantifying the relative impacts of vegetation cover and urban development on surface temperature patterns in these environments remain limited (Estoque et al., 2017; Zhang et al., 2021).

Land surface temperature is fundamentally governed by the interplay of surface biophysical properties, notably vegetation density and the extent of built-up infrastructure (Guha, Govil, Dey, & Gill, 2018; Weng & Lu, 2008). Vegetation moderates surface temperatures through shading and evapotranspiration. In contrast, impervious surfaces, such as roads and buildings, tend to retain and re-radiate heat due to low albedo and high thermal capacity (Li, Schubert, Kropp, & Rybski, 2020; Zou, Yang, & Qiu, 2019). Remotely sensed indices provide robust proxies for these characteristics: the normalised difference vegetation index (NDVI) effectively captures vegetation vigour and density, while the normalised difference built-up index (NDBI) delineates urban structural intensity. Numerous studies conducted in temperate and semi-arid regions have consistently documented inverse relationships between NDVI and LST, alongside positive associations between NDBI and LST (Cetin et al., 2024; Kikon, Kumar, & Ahmed, 2023). Similar patterns are observed in tropical contexts. For instance, seasonal analyses in Raipur City, India, reveal strong inverse NDVI–LST correlations (−0.63 in the post-monsoon period) and consistent NDBI–LST relationships (Guha & Govil, 2020). Geographically weighted regression in Chinese cities revealed that NDBI explains LST variability more strongly than other indices (Xiang et al., 2023). Global studies further indicate that NDVI exhibits a moderate positive correlation with LST (+0.57), while NDBI is more negatively associated (−0.52), depending on land cover context (Rahimi, Dong, & Jung, 2025). Additionally, NDBI has been shown to maintain a more stable relationship with LST than NDVI in urban tropical areas (Guha, Govil, Taloor, Gill, & Dey, 2022). However, empirical

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evidence from humid tropical cities remains comparatively sparse, and the unique climatic regimes, characterised by high baseline humidity and frequent rainfall, may alter these relationships.

In Malaysia, empirical UHI research has frequently focused on the capital region, but several significant investigations in other urban settings enhance contextual relevance. Kubota and Ossen (2009) assessed Johor Bahru using field measurements and recorded nocturnal UHI intensity of approximately 4 °C, noting that open spaces functioned as cooling "islands" that interrupted UHI zones. In Putrajaya, Morris et al. (2015) employed mesoscale modelling and found nighttime UHI ranges between 1.9 °C and 3.1 °C, with an average daily intensity of about 0.79 °C. Penang's Tanjong City Marina and Jetty District study, as noted by Karsono and Wahid (2010), linked building materials and urban layout to localised heat accumulation. In the Cameron Highlands, Ibrahim, Latiff, Ismail, and Isa (2018) identified UHI formation concentrated around the city centre via field surveys and spatial analysis, and How, Ismail, and Muharam (2020) showed a substantial ~2 °C increase in land surface temperature (LST) over 2009–2019 due to land-use changes.

Johor Bahru, situated at the southern tip of Peninsular Malaysia, reflects the pressures of tropical urbanisation, having undergone extensive land conversion from natural and agricultural landscapes to residential, commercial, and industrial uses over recent decades (Kang & Kanniah, 2022; Tew & Tan, 2020). Yet, despite these pronounced land cover shifts, localised studies explicitly quantifying how vegetation and urban structures interact to influence LST within the city are lacking. This gap restricts the capacity of urban planners and policy makers to formulate targeted interventions that mitigate heat accumulation and enhance urban resilience. This study addresses the lack of spatially explicit quantification of how vegetation cover and built-up intensity shape land surface temperature in a humid tropical urban setting. Without such empirical insights, a critical limitation remains in efforts to design and implement urban heat mitigation strategies tailored to the local biophysical context. The findings hold significance for guiding evidence-based urban planning and informing the strategic integration of green infrastructure to optimise thermal regulation, ultimately contributing to the formulation of more climate-resilient cities in the tropics.

2.0 Materials and Methods

2.1 Study Area

The study area encompasses Johor Bahru, the capital of Johor state, situated at the southernmost tip of the Malaysian Peninsula. For this analysis, a spatial extent was delineated by applying a 15 km buffer around the city centre (approximately at 1.49°N, 103.75°E), effectively capturing Johor Bahru and its surrounding peri-urban zones (Figure 1). This region lies between latitudes 1.45°N and 1.60°N, and longitudes 103.60°E and 103.80°E. It is characterised by a humid equatorial climate, with mean annual temperatures typically ranging from 27°C to 28°C and average yearly rainfall exceeding 2,000 mm. Over the past two decades, Johor Bahru has undergone substantial urban expansion, converting extensive areas of vegetated and agricultural land into residential, commercial, and industrial uses. These dynamics make it a representative setting for investigating the interactions among vegetation cover, built-up intensity, and land surface temperature within a rapidly urbanising tropical environment.

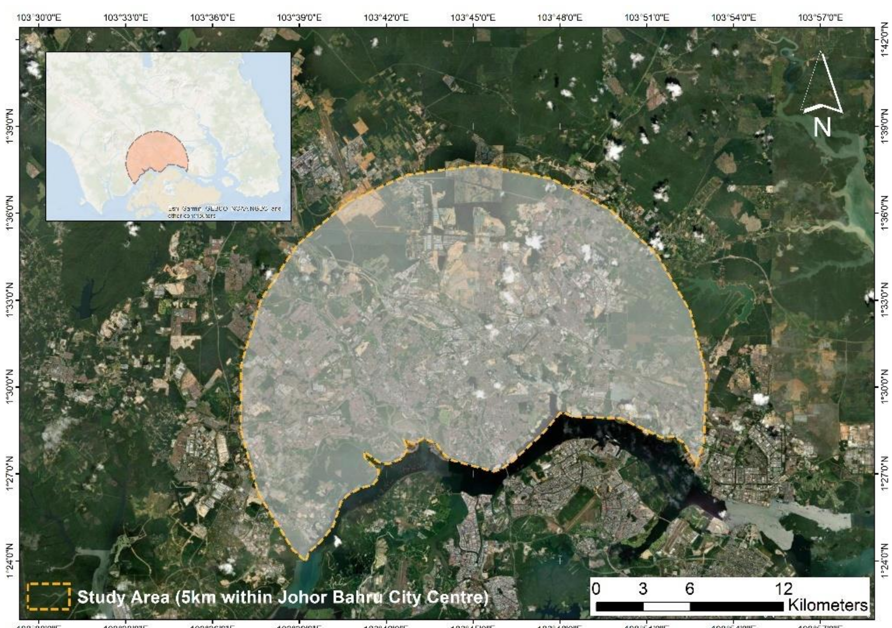


Figure 1: Map of study area

2.2 Data Sources and Method

2.2.1 Satellite Imageries

This study employed multi-year Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imagery accessed via the Google Earth Engine platform. Images were filtered for cloud cover (<30%) over the Johor Bahru region and composited across multiple years to ensure robust spatial coverage. Spectral bands were pre-processed by applying radiometric calibration and atmospheric correction coefficients provided in the Landsat Collection 2 Level-2 data.

2.2.2 Derivation of NDVI, NDBI, and LST

In this study, Landsat 8 OLI and TIRS imagery were utilised to derive the key indices required to assess the influence of vegetation cover and urbanisation on LST in Johor Bahru, Malaysia. The workflow involved calculating NDVI and NDBI from the OLI spectral bands and retrieving LST estimates from the TIRS thermal data. All image processing and index derivations were performed in Google Earth Engine, while spatial analyses and mapping were conducted using ArcGIS Pro.

The NDVI was computed to characterise vegetation cover, employing the standard formulation as in equation (1):

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \qquad (1)$$

where NIR refers to Band 5 (0.85–0.88 μm) and RED to Band 4 (0.64–0.67 μm) of Landsat 8 OLI, values closer to +1 indicate dense vegetation. In contrast, values near zero or negative typically represent built-up areas or water bodies.

The NDBI was calculated to quantify built-up intensity, using equation (2):

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \qquad (2)$$

where SWIR denotes Band 6 (1.57–1.65 μm) and NIR again corresponds to Band 5. Higher NDBI values are associated with impervious surfaces, facilitating the identification of urbanised zones.

LST was retrieved from the Landsat 8 OLI and TIRS Collection 2 Level-2 dataset, which provides atmospherically corrected surface temperature estimates as part of its standardised products. Specifically, the thermal band (Band 10) was employed, representing surface temperature values stored as scaled digital numbers. Following the USGS Collection 2 specifications, these were converted to absolute temperature in Kelvin using the radiometric rescaling factors provided in the metadata (Speiser & Largier, 2024; Thammaboribal, Triapthti, & Lipiloet, 2025):

$$LST(K) = Q_{cal}\ x\ M_L + A_L \qquad (3)$$

where Q_{cal} is the pixel value of Band 10, M_L=*0.00341802* is the multiplicative scaling factor, and A_L=*149.0* is the additive offset. This formulation yields LST values that are already corrected for atmospheric effects and surface emissivity, based on an operational split-window algorithm applied by the USGS.

2.3 Sampling and Statistical Analysis

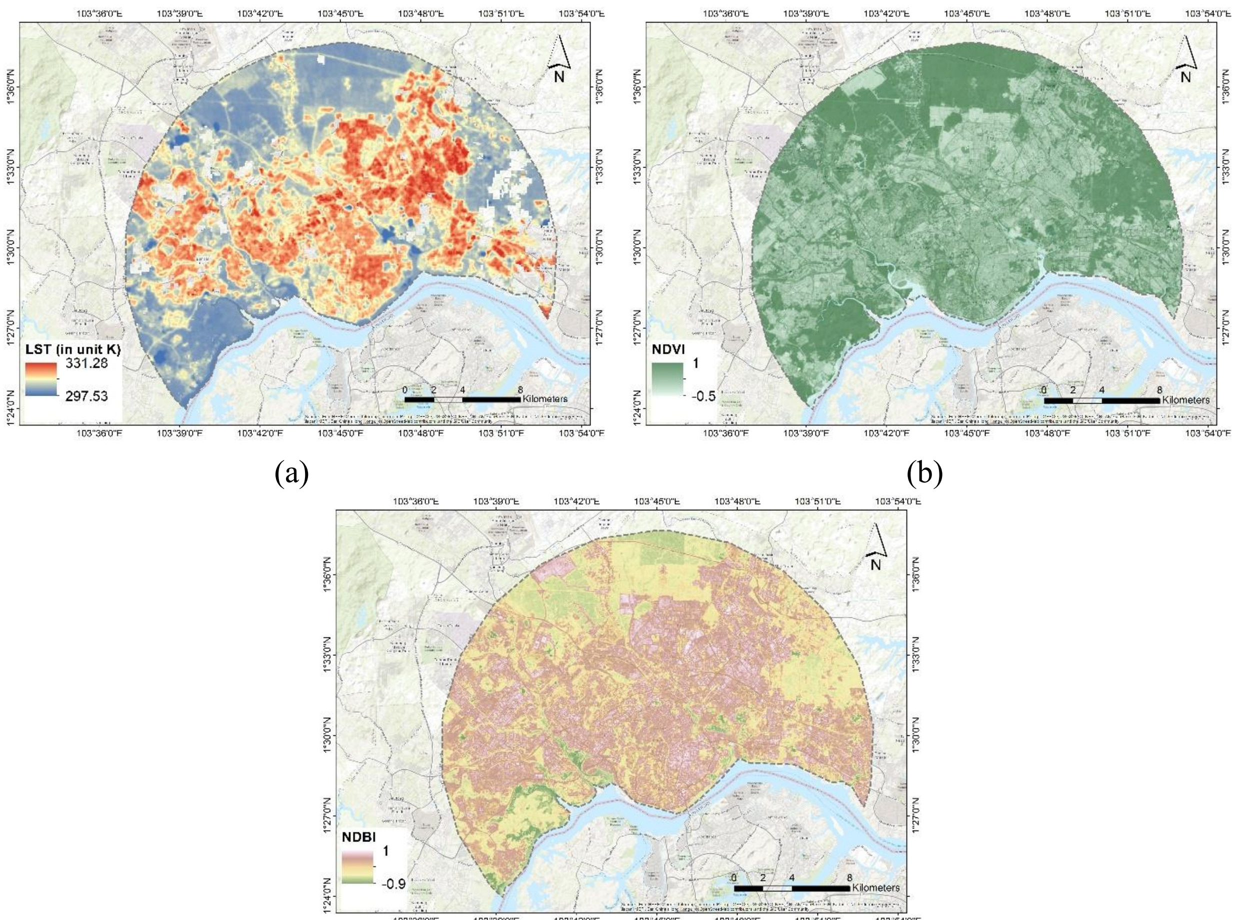
To quantify the relationships between LST, vegetation cover, and built-up intensity, a random sampling approach was employed on the composite dataset of NDVI, NDBI, and LST across the study area. This approach ensures an unbiased representation of spatial heterogeneity and allows efficient statistical modelling while managing computational demands. Such pixel-level sampling and regression analyses are consistent with methodologies widely adopted in urban thermal studies to elucidate the influence of land cover characteristics on surface temperatures (Li et al., 2017; Weng, 2009). Sampling was performed using Google Earth Engine's sample function, which efficiently extracts attribute values without retaining geometric information, thereby optimising the dataset for subsequent statistical analysis. This sampling approach, which retrieves attribute values without retaining geometry, is consistent with established practices in urban thermal remote sensing studies that utilise pixel-wise data extraction to quantify statistical relationships among land surface temperature, vegetation cover, and built-up intensity (Mudele & Gamba, 2019; Tran, Uchihama, Ochi, & Yasuoka, 2006). The resulting dataset formed the basis for subsequent correlation and regression analyses to examine the influence of vegetation and impervious surfaces on urban thermal patterns.

By employing a sufficiently large and spatially distributed sample size, the methodology ensured robust capture of variability in surface temperature, vegetation density, and built-up characteristics across different urban morphologies. This dataset formed the basis for simple and multiple regression analyses, enabling quantification of the influence of vegetation and impervious surfaces on urban thermal patterns.

3.0 Results and Analysis

3.1 Spatial Mapping of LST, NDVI, and NDBI

To complement the regression analysis and provide spatial context to the observed statistical relationships, thematic maps of LST, NDVI, and NDBI were produced (Figure 2).



(a) (b)

(c)

Figure 2: Spatial distribution maps over the study area derived from 30-m resolution Landsat 8 imagery: (a) Land Surface Temperature (LST) in Kelvin (K), (b) Normalised Difference Vegetation Index (NDVI), and (c) Normalised Difference Built-up Index (NDBI).

These maps reveal clear spatial heterogeneity, with surface temperatures closely tied to variations in land cover. Areas with high NDBI values, indicating dense built-up surfaces, correspond to distinct thermal hotspots, while regions with higher NDVI show cooler temperatures, underscoring the moderating effect of vegetation identified in the models. Transitional zones along the urban fringe, marked by intermediate NDVI and NDBI levels, indicate areas where targeted greening could help mitigate localised heat accumulation. Taken together, these spatial patterns and statistical findings offer a more integrated understanding of how vegetation and urban development jointly influence thermal conditions across the study area.

3.2 Descriptive Statistics and Correlation Analysis

Descriptive statistics presented in Table 1 summarise the distributions of NDVI, NDBI, and LST across the study area. NDVI values ranged from -0.41 to 0.92 (mean = 0.52, SD = 0.25), indicating a heterogeneous landscape comprising both densely vegetated patches and sparsely vegetated or impervious zones.

NDBI values were predominantly negative, spanning -0.66 to 0.20 (mean = -0.15, SD = 0.19), reflecting the dominance of low to moderate built-up intensity across the region. Meanwhile, LST varied from 304.3 K to 324.2 K (mean = 313.2 K, SD = 4.3 K), which is characteristic of urban thermal conditions in tropical environments. The correlation matrix in Table 1 further shows the interrelationships among these variables. A moderate negative correlation was observed between NDVI and LST (r = -0.50), suggesting that areas with greater vegetation cover tended to exhibit lower surface temperatures. Conversely, NDBI demonstrated a strong positive association with LST (r = 0.75), underscoring the pronounced warming effect of built-up surfaces. Additionally, NDVI and NDBI were inversely correlated (r = -0.70), consistent with the expected spatial trade-off between vegetative and impervious land cover types in urban settings.

Table 1. Descriptive statistics and Pearson correlation coefficients (*r*) for NDVI, NDBI, and LST (K), with *n* = 500

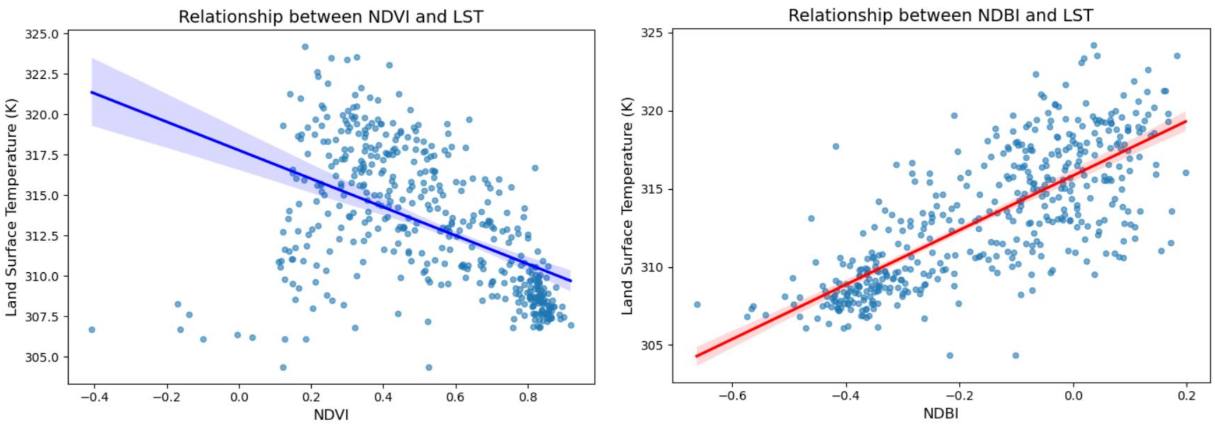
Variable	Mean	SD	Min	Max	Corr. with NDVI	Corr. with NDBI	Corr. with LST
NDVI	0.52	0.25	-0.41	0.92	1.00	-0.70	-0.50
NDBI	-0.15	0.19	-0.66	0.20	-0.70	1.00	0.75
LST	313.2	4.30	304.3	324.2	-0.50	0.75	1.00

These findings align with broader regional and global studies. For example, Zhou et al. (2016) documented similar patterns across 32 major Chinese cities, reporting inverse correlations between NDVI and urban heat island (UHI) intensity (r ≈ -0.62) and positive correlations between impervious surfaces and UHI ($r \approx 0.66$). In a tropical context, Buyadi, Mohd, and Misni (2013) found that extensive vegetation loss (~68% reduction over three decades) in Kuala Lumpur was accompanied by an increase in mean LST from 22.9°C to 26.2°C. Despite relatively modest coefficients of determination ($R^2 \approx 0.08–0.10$), their analyses revealed statistically significant inverse relationships between NDVI and LST ($p < 0.05$). Moreover, these patterns are consistent with the foundational synthesis by Voogt and Oke (2003), who emphasised that LST derived from thermal remote sensing is highly responsive to variations in vegetation and built-up surfaces, typically exhibiting inverse relationships with NDVI and positive associations with impervious area metrics. Collectively, these parallels underscore the suitability of NDVI and NDBI as explanatory indicators for assessing spatial variability in urban thermal environments.

3.3 Simple Linear Regression Models

Simple linear regression models were first employed to quantify the independent influences of vegetation cover (NDVI) and built-up intensity (NDBI) on LST. According to Table 2 and Figure 3, when NDVI was used as the sole predictor, the model yielded an adjusted R^2 of 0.253 ($p < 0.001$), indicating that NDVI alone accounted for roughly 25% of the spatial variability in LST. The negative regression coefficient (-8.80, $p < 0.001$) suggests that a one-unit increase in NDVI is associated with an estimated decrease of 8.8 K in LST, underscoring the crucial cooling effect of vegetation in urban settings.

In contrast, the model incorporating NDBI as the sole predictor exhibited substantially greater explanatory power, achieving an adjusted R^2 of 0.568 ($p < 0.001$). The positive coefficient (17.46, $p < 0.001$) indicates that each unit increase in NDBI corresponds to an approximate 17.5 K rise in LST, highlighting the pronounced warming impact of impervious surfaces. Together, these results reinforce the bivariate correlations observed earlier, emphasising the dominant role of built-up areas in elevating surface temperatures while also demonstrating the mitigating influence of vegetation when considered independently.



(a) (b)

Figure 3: Relationships between land surface temperature (LST) and (a) normalised difference vegetation index (NDVI) and (b) normalised difference built-up index (NDBI)

Table 2: Summary of linear regression results examining the relationships between vegetation cover (NDVI) and built-up intensity (NDBI) with land surface temperature (LST) in Johor Bahru.

Metric	NDVI vs LST	NDBI vs LST
Adjusted R^2	0.253	0.568
F-statistic (p-value)	154.2 (<0.001)	595.3 (<0.001)
AIC	2477	2229
BIC	2485	2237
Durbin-Watson	2.064	1.998
Constant Coef. (SE)	317.78 (0.41)***	315.85 (0.17)***
NDVI Coef. (SE)	-8.80 (0.71)***	-
NDBI Coef. (SE)	-	17.46 (0.72)***
t-value	-12.42	24.40
p-value	<0.001	<0.001
95% CI	[-10.19, -7.40]	[16.05, 18.86]
Jarque-Bera p	<0.001	0.145
Skew / Kurtosis	-0.49 / 4.06	0.05 / 3.44

3.4 Multiple Regression Analysis

Building on the simple regressions, multiple regression analyses were performed to evaluate the combined and interactive influences of NDVI and NDBI on LST. The initial additive model, incorporating both NDVI and NDBI as independent predictors, accounted for approximately 57% of the variance in LST (adjusted $R^2 = 0.568$, $p < 0.001$). In this framework, NDBI emerged as a strong and statistically significant driver of LST ($\beta = 18.28$, $p < 0.001$), whereas NDVI no longer exhibited a significant independent effect ($\beta = 0.88$, $p = 0.245$) after controlling for built-up intensity. Variance inflation factors (VIF ≈ 1.98) indicated low multicollinearity, supporting the robustness of these estimates.

To assess whether the cooling influence of vegetation varies with urban intensity, an interaction term (NDVI × NDBI) was introduced, as shown in Table 3. Including this term modestly improved model fit (adjusted $R^2 = 0.579$, $p < 0.001$) and revealed significant effects for all predictors. The positive interaction coefficient ($\beta = 11.57$, $p < 0.001$) suggests that NDVI's impact on LST is contingent upon NDBI, indicating a compounded relationship where the temperature-moderating role of vegetation is moderated by surrounding impervious surfaces. Diagnostic checks, including Durbin-Watson statistics near 2.0 and non-significant Jarque-Bera p-values, revealed no significant concerns regarding autocorrelation or residual normality. Collectively, these findings underscore the necessity of accounting for interactive effects in urban thermal studies, demonstrating that while vegetation generally mitigates surface temperatures, its effectiveness is markedly influenced by the extent of built-up cover.

Table 3: Comparison of multiple regression models predicting land surface temperature (LST) using NDVI, NDBI, and their interaction

Model	Adj. R^2	NDVI Coef. (p)	NDBI Coef. (p)	NDVI×NDBI Coef. (p)	AIC	BIC
NDVI + NDBI	0.568	0.88 (0.245)	18.28 (<0.001)	—	2230	2242
NDVI + NDBI + NDVI×NDBI	0.579	4.17 (0.001)	13.69 (<0.001)	11.57 (<0.001)	2219	2236

The interaction surface shown in Figure 4 further illustrates these dynamics by mapping predicted LST across varying combinations of NDVI and NDBI. The plot reveals that LST increases sharply with rising NDBI across all levels of NDVI, underscoring the dominant warming role of impervious surfaces. Meanwhile, the cooling influence of NDVI is most pronounced in areas with low built-up intensity; here, higher vegetation cover is associated with substantial reductions in LST. However, this mitigating effect diminishes considerably in highly urbanised zones, where even significant increases in NDVI result in only modest temperature decreases. These patterns emphasise that the capacity of vegetation to offset urban heat is not uniform but strongly influenced by the surrounding built environment.

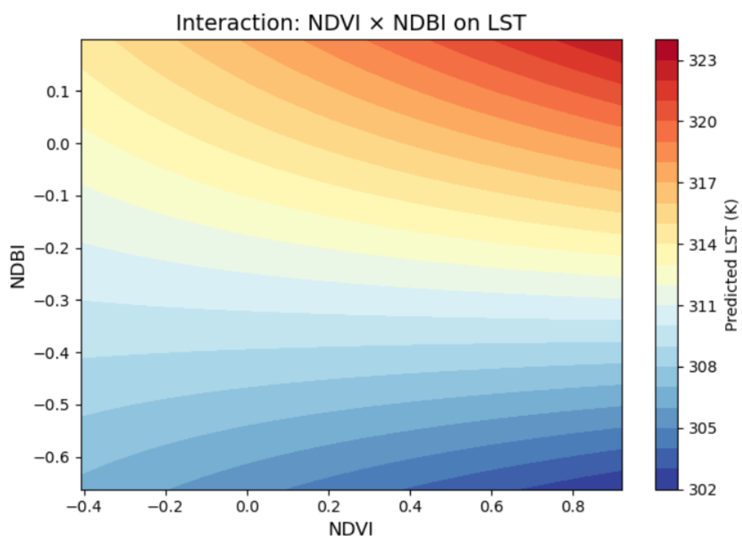


Figure 4: Interaction surface illustrating the combined effects of NDVI and NDBI on predicted LST based on the multiple regression model with an interaction term

4.0 Discussion

The results confirm that vegetation exerts a strong cooling influence on surface temperatures. NDVI was negatively correlated with LST (r = –0.50), and regression analysis revealed that a one-unit increase in NDVI corresponded to an estimated 8.8 K reduction in LST. This outcome is consistent with earlier findings in Kuala Lumpur (Buyadi et al., 2013) and global syntheses by Voogt and Oke (2003), which emphasise the role of vegetation in reducing urban heat through shading and evapotranspiration. However, in multiple regression models, the independent effect of

NDVI was diminished once NDBI was considered, suggesting that vegetation's cooling capacity is strongly conditioned by the surrounding built environment.

Built-up intensity emerged as the dominant driver of elevated LST. NDBI showed a strong positive correlation with LST ($r = 0.75$), and regression models indicated a 17.5 K rise in LST for each unit increase in NDBI. This effect was more than twice the magnitude of the vegetation's cooling influence. These results align with those of Zhou et al. (2016), who reported comparable associations between impervious cover and urban heat island intensity in major Chinese cities. In the tropical context of Johor Bahru, the thermal effects of impervious materials are amplified by persistent solar loading and high humidity.

The inclusion of an NDVI × NDBI interaction term improved model performance (adjusted $R^2 = 0.579$), revealing that vegetation's cooling benefits are contingent on urban density. In less urbanised zones, higher NDVI corresponded to substantial reductions in LST, while in dense built-up areas, the cooling effect diminished considerably. This interaction highlights the contextual nature of urban heat mitigation: greening is most effective in low- to medium-density areas but less impactful in compact urban cores dominated by impervious surfaces.

The findings carry practical implications for climate-sensitive urban design. At the urban fringe, expanding vegetation cover can substantially reduce localised heat accumulation. In dense city centres, however, mitigation requires complementary strategies, such as reflective or permeable materials, vertical greening, or improved urban ventilation. A balanced approach that integrates both increased vegetation and modifications to built-up surfaces is therefore essential for managing thermal stress in tropical cities. In summary, the study confirms the opposing roles of vegetation and impervious cover in shaping urban thermal environments and demonstrates that their effects are not independent but interactive. While greening is effective in reducing LST, its efficacy is significantly influenced by the intensity of built-up areas. Urban heat mitigation in tropical cities thus requires integrated planning that couples green infrastructure with strategies to reduce the thermal burden of impervious surfaces.

5.0 Conclusion

This study highlights how vegetation cover and built-up intensity jointly shape the spatial variability of land surface temperature in Johor Bahru, a rapidly urbanising tropical city. While vegetation contributes to cooling through evapotranspiration and shading, the dominant warming effect of impervious surfaces often overshadows this influence, particularly in dense urban cores. The interaction between NDVI and NDBI underscores that vegetation's cooling benefit is not uniform but contingent on the extent of surrounding built-up development. From a planning perspective, these findings emphasise the need for integrative urban heat mitigation strategies. Expanding vegetation cover remains critical, especially along urban fringes and in low- to medium-density zones, where cooling benefits are most pronounced. However, in compact urban centres, effective heat reduction will require complementary measures, including reflective or permeable materials, vertical greening, and improved ventilation corridors. Urban design policies that balance green infrastructure with thoughtful control of impervious surface expansion are essential for creating thermally resilient tropical cities.

Future research should build on this analysis by incorporating higher-resolution datasets and additional variables such as albedo, building morphology, and soil moisture, as well as examining seasonal and long-term trends. Such work would enable more precise modelling of urban thermal dynamics and support adaptive planning in response to climate change. In conclusion, the study demonstrates that mitigating urban heat in tropical environments demands not only enhancing green infrastructure but also strategically managing urban form and land use patterns. Tailored, context-specific interventions are therefore crucial to ensure sustainable and climate-resilient urban development in rapidly transforming regions like Johor Bahru.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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