

The Impact of Urbanization Scale on Ecological Conditions and Surface Heat Patterns: A Comparative Study of Jakarta – Semarang City

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ABSTRAK

Urbanisasi mengubah komposisi dan distribusi spasial permukaan terbangun dan vegetasi, yang memengaruhi kondisi termal perkotaan. Namun, kajian komparatif pada skala urbanisasi yang berbeda yang menghubungkan karakteristik permukaan tersebut dengan partisi energi masih terbatas. Penelitian ini membandingkan Jakarta dan Kota Semarang untuk mengkaji perbedaan kondisi termal dan ekologis permukaan terkait dengan perbedaan skala urbanisasi. Citra Landsat 9 digunakan untuk memperoleh suhu permukaan lahan (LST), *Normalized Difference Vegetation Index* (NDVI), *Normalized Difference Built-up Index* (NDBI), dan *Urban Thermal Field Variance Index* (UTFVI). *Random Forest* digunakan untuk mengklasifikasikan tutupan lahan, sedangkan *Surface Energy Balance Algorithm for Land* (SEBAL) digunakan untuk mengestimasi komponen neraca energi permukaan. Analisis regresi digunakan untuk mengkaji hubungan NDVI dan NDBI dengan UTFVI, sedangkan uji Mann-Whitney U digunakan untuk menguji perbedaan antarkota. Jakarta memiliki rata-rata NDBI lebih besar (-0,046) dan rata-rata NDVI lebih rendah (0,225) dibandingkan Kota Semarang (-0,180 dan 0,402). Jakarta memiliki LST rata-rata lebih tinggi (28,7 °C), dengan hanya 17,95% wilayah tergolong sangat baik, dibandingkan 26,2 °C dan 74,68% di Kota Semarang. NDBI menunjukkan hubungan yang lebih kuat dengan UTFVI ($R^2 \approx 0,56$) dibandingkan NDVI ($R^2 \approx 0,32$). Regresi berganda menunjukkan NDBI meningkatkan UTFVI lebih kuat di Jakarta dan NDVI menurunkan UTFVI lebih kuat di Kota Semarang. Jakarta memiliki fluks panas teras rata-rata lebih tinggi (141,41 W/m²), sedangkan Kota Semarang memiliki fluks panas laten rata-rata lebih tinggi (142,91 W/m²). Temuan ini menunjukkan bahwa skala urbanisasi memengaruhi kondisi termal melalui perbedaan komposisi, distribusi spasial permukaan, dan partisi energi, sehingga mendukung strategi mitigasi panas perkotaan yang kontekstual.

Kata kunci: Tutupan Lahan, Suhu Permukaan Tanah, Neraca Energi Permukaan, Urbanisasi, UTFVI

ABSTRACT

Urbanization alters the composition and spatial distribution of built-up and vegetated surfaces, influencing urban thermal conditions. However, comparative assessments across different urbanization scales that link these surface characteristics with energy partitioning remain limited. This study compares Jakarta and Semarang City to examine differences in surface thermal and ecological conditions associated with contrasting urbanization scales. Landsat 9 imagery was used to derive land surface temperature (LST), Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Urban Thermal Field Variance Index (UTFVI). Random Forest classified land-cover, while Surface Energy Balance Algorithm for Land (SEBAL) estimated surface energy balance components. Regression analysis examined NDVI and NDBI relationships with UTFVI, and Mann-Whitney U tests assessed differences between cities. Jakarta had greater mean NDBI (-0,046) and lower NDVI (0,225) than Semarang City (-0,180 and 0,402, respectively). Jakarta exhibited higher mean LST (28,7 °C), with 17,95% of its area classified as very good, compared with 26,2 °C and 74,68% in Semarang City. NDBI showed a stronger relationship with UTFVI ($R^2 \approx 0,56$) than NDVI ($R^2 \approx 0,32$), while multiple regression indicated a stronger association between NDBI and higher UTFVI in Jakarta and between NDVI and lower UTFVI in Semarang City. Despite comparable mean net radiation, Jakarta had higher mean sensible heat flux (141,41 W/m²), whereas Semarang City had higher mean latent heat flux (142,91 W/m²). These findings demonstrate that urbanization scale affects thermal conditions through contrasting surface composition, spatial distribution, and energy partitioning, supporting context-specific heat mitigation.

Keywords: Land Cover, Land Surface Temperature (LST), Surface Energy Balance, Urbanization, UTFVI

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1. INTRODUCTION

UHI is commonly characterised by a situation where temperatures in city's center are greater than its surrounding areas. When it comes to population growth and populated cities, UHI can become a critical issue due to its impact on many aspects of life, especially human health and ecological conditions. For example, the World Health Organization (WHO, 2025) has reported a correlation between heat risk and cardiovascular, respiratory disorders, mental health problems, and increased risks of accidents and infectious disease transmission. The rising temperatures also worsen mortality, morbidity, and reduce cognitive performance (Meadows et al., 2024; Mazloumi et al., 2014). These risks underscore the urgent need to address UHI impacts in densely populated areas.

High-population-density areas, especially metropolitan or megapolitan cities like Jakarta and Semarang City, experience more frequent heat stress in daily life. Rapid urbanisation tends to add more impervious facilities like buildings, roads, and settlements. This can change the albedo and the arrangement of energy on the ground (Soeparyanto et al., 2022). These factors will lead to more heat being absorbed in the area, thus raising the temperature, thereby increasing the potential for damage to the natural world (Soeparyanto et al., 2022; Januari et al., 2024). One of the famous approaches to address these challenges is the oversight of green areas in the downtown.

Previous studies have mentioned that urban open greenery is very important due to its ability to absorb carbon dioxide (CO₂) and enhance oxygen (O₂) levels in the air. Moreover, it's also important for reducing air temperature, improving thermal comfort, and providing cultural ecosystem service to urban communities (Saninah et al., 2023). Additionally, factors specific to each city, including density of population, land use, and the effects of UHI can greatly influence the effectiveness of urban green open spaces, indicating that mitigation approaches for the UHI effect might differ in each city (Yang et al., 2022). Hence, mitigation strategies should be addressed to a specific city's condition.

Although both Jakarta and Semarang are major urban centers in Indonesia, they represent contrasting scales of urbanization and physical development. As the national capital, Jakarta recorded over 10 million residents in the 2020 census, with a high population density of 14,555 people/km² (BPS DKI Jakarta, 2021). Consequently, the megacity has experienced significant environmental degradation and rising urban temperatures over recent decades (Syamsudin & Lestari, 2017). In contrast, Semarang City, the provincial capital of Central Java, represents a smaller-scale urban center with approximately 1.6 million residents and a population density of 4,425 people/km² (BPS Kota Semarang, 2021).

Urban thermal conditions are strongly influenced by localized land-surface characteristics and urban dynamics (Ramamurthy and Bou-Zeid, 2017). Cities may therefore exhibit different thermal responses even at comparable urban scales. Differences in vegetation cover and built-up surfaces have been associated with contrasting UHI intensities in metropolitan areas such as Delhi and Mumbai, despite their comparable city sizes (Grover and Singh, 2015). Furthermore, urban landscape composition and spatial configuration can influence variations in urban thermal conditions (Chen and Yu, 2017). These findings indicate that the thermal implications of urbanization are closely related not only to the overall scale of urban development but also to how built-up and vegetated surfaces are distributed and combined within an urban area.

The Normalized Difference Built-up Index (NDBI) and Normalized Difference Vegetation Index (NDVI) provide complementary indicators for characterizing built-up and vegetated surfaces, respectively (Sitasi Macarof and Statescu, 2017). NDBI describes the spatial characteristics of built-up surfaces associated with urban development, whereas NDVI represents the distribution and condition of vegetation associated with ecological condition. Examining these indicators together provides a basis for assessing how differences in surface composition correspond to variations in urban thermal and ecological conditions. NDVI and NDBI are widely used to characterize vegetation and built-up surfaces, respectively, making them relevant indicators for representing the dominant surface characteristics of urban environments and examining their relationship with thermal conditions.

Although Jakarta and Semarang City have been widely studied in relation to urban thermal conditions, existing studies have generally examined the two cities separately rather than within a common comparative framework. This limits understanding of how contrasting urbanization scales and associated differences in the proportion and spatial distribution of built-up and vegetated surfaces contribute to differences in surface thermal conditions. Previous studies have also widely examined the relationships between land-cover characteristics and LST, while the associated surface energy partitioning remains less explored in comparative assessments of cities with different urbanization contexts. Understanding these energy pathways is important because surface energy partitioning determines how available energy is distributed between sensible and latent heat flux, providing a mechanistic basis for interpreting differences in thermal conditions and informing context-specific mitigation strategies.

Therefore, this study aims to examine how contrasting urbanization scales are associated with differences in ecological and thermal conditions in Jakarta and Semarang City by comparing built-up and vegetation characteristics using NDBI, NDVI, LST and UTFVI. Surface energy balance components are

further compared to explain differences in energy partitioning between the two cities and provide a basis for discussing context-specific urban heat mitigation.

2. MATERIALS AND METHODS

This investigation utilises an approach known as comparative studies that incorporates conventional telemetry data and statistical methods to quantify the differences in urban heat impacts between two distinct urbanization scales.

2.1. Location of Study Areas

This study was observed on Jakarta and Semarang City areas (Figure 1). Geographically, Jakarta is situated on the northwest coast of Java Island, precisely between $6^{\circ}10' - 6^{\circ}22' S$ and $106^{\circ}44' - 106^{\circ}58' E$, whereas Semarang City is situated on the island's northern central coast between $6^{\circ}50' - 7^{\circ}10' S$ and $110^{\circ}15' - 110^{\circ}35' E$. The differences in urbanization scale, land cover configuration, and

anthropogenic pressure make them suitable for comparative analysis of UHI's impacts.

2.2. Data

The primary dataset comprised of Landsat 9 Collection 2 Level 2 images taken in 2024 acquired from the USGS. Two avail scenes for each study area were averaged because identical acquisition dates for Jakarta and Semarang City were unavailable. This approach should be able to minimize temporal variation and assure comparability between cities, consistent with a previous study, which recommended using multiple scenes within one period to avoid reliance on a single potentially biased acquisition (Knudby et al., 2014).

To validate Landsat-derived LST, Moderate Resolution Imaging Spectroradiometer (MODIS) MOD11A2.061 products were used as reference. Administrative boundaries were gained from the Indonesian Geospatial Information Agency (BIG) for delineating study areas. All datasets used are outline in Table 1.

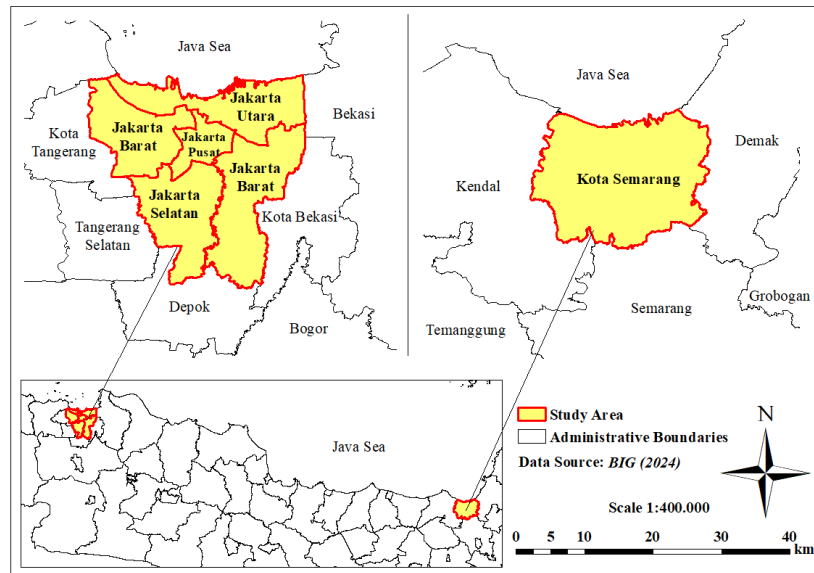


Figure 1. Study Area Locations of Jakarta (Megacity) and Semarang City (Metropolitan City), Indonesia. Administrative Boundaries were obtained from BIG (2024)

Table 1. Summary of Datasets used in this Study

Data	Spatial Resolution	Period	Utility	Sources
Citra Landsat 9 OLI-2/TIRS-2	30 m	Jakarta: 30-Jul-24 15-Aug-24 (path 122/row 64)	- Ecological condition analysis (UTFVI, NDBI, NDVI) - Land cover classification - Energy balance component analysis	USGS
		Semarang City: 16-Jul-24 17-Aug-24 (path 120/row 65)		
LST Citra MODIS MOD11A2.061	1 km	Jakarta: 27-Jul-24 12-Aug-24	Validation of estimated surface temperature data	USGS
		Semarang City: 19-Jul-24 12-Aug-24		
Regional Administrative Boundaries			Study area boundaries	BIG

Both Landsat and MODIS scenes were averaged due to different acquisition dates.

2.3. Data Processing and Analysis

The research procedure began with the acquisition of surface temperature data from Landsat 9 OLI-2/TIRS-2 and MODIS LST imagery, which were processed using cloud masking. The data were later clipped to fit the administrative limits of both cities involved in the study. A research workflow chart is summary in Figure 2.

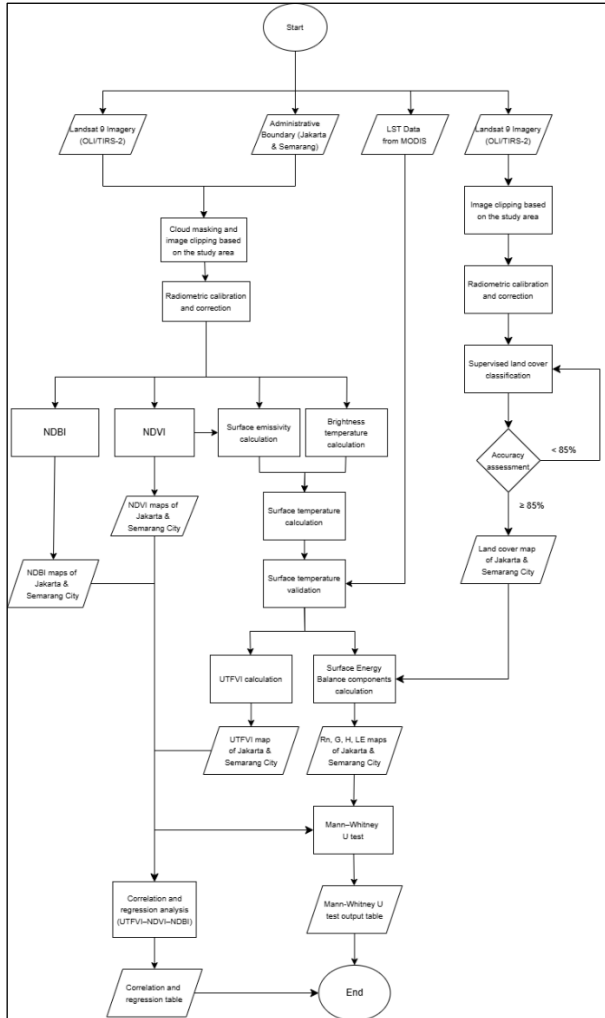


Figure 2. Research Flowchart

2.3.1. Image Processing and Classification

The technique known as the Random Forest was used to oversee the grouping based on land cover, with a proportion of training and test samples of 80:20 referring to the research of Adhitya et al. (2023). The classification consists of four classes: water bodies, vegetation, open land, and built-up land. These four classes were selected to simplify the classification structure and reflect the dominant landscape elements typical of the urban area studied. The amount of sample points was calculated based on Eq. 1 (Imron, 2017).

$$n = \frac{N}{(N.e^2) + 1} \quad (1)$$

where n refers to the number of samples, N denotes study area size, and e is an error margin (5%). Samples for training and testing purposes were carefully selected by utilizing the imagery available on Google Earth, representing land cover classes such as vegetation, built-up areas, water, and bare soil

The correctness in coverage of land grouping was verified through the use of a confusion matrix or error matrix that was subsequently employed to compute user's, producer's, overall, and kappa accuracy. The confusion matrix can be viewed in Table 2. The formulas for computing the above measures are provided in Eqs. 2–5 (Novianti 2021).

Table 2. Confusion Matrix

Land Cover Class Result	Actual Class			
	A	B	C	D
A	X_{ii}			
B		X_{ii}		
C			X_{ii}	
D				X_{ii}
Total	X_{i+}			N

User's accuracy:

$$(X_{ii}/X_{i+}) \times 100\% \quad (2)$$

Producer's accuracy:

$$(X_{ii}/X_{i+}) \times 100\% \quad (3)$$

Overall accuracy:

$$((\sum_{i=1}^r x_{ii})/N) \times 100\% \quad (4)$$

Kappa accuracy:

$$[(N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r x_{i+} x_{+i}) / (N^2 - \sum_{i=1}^r x_{i+} x_{+i})] \times 100\% \quad (5)$$

where N denotes the total number of pixels in the image; X_{i+} represents the sum total of pixels in row i; X_{+i} refers to the sum total of pixels in column i; X_{ii} represents the diagonal element of the contingency matrix for row i and column i

NDVI (Eq. 6) and NDBI (Eq. 7) were calculated to quantify vegetation cover and built-up intensity, respectively, with their classifications shown in Table 3 and Table 4.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (6)$$

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \quad (7)$$

where NIR, RED, and SWIR1 denote the near-infrared, red, and shortwave infrared band reflectances.

Table 3. NDVI Classification. Higher Values of NDVI Indicate Denser Vegetation Cover and Better Ecological Health

NDVI Value	Classification
$NDVI < 0$	Non-Vegetation
$0 \leq NDVI < 0,154$	Very Low Greenness
$0,154 \leq NDVI < 0,241$	Low Greenness
$0,241 \leq NDVI < 0,431$	Moderate Greenness
$NDVI \geq 0,431$	High Greenness

Source: modified from (Isnaeni and Prasetyo, 2021).

Table 5. Categories of Ecological Conditions and UHI Existence based on UTFVI

UTFVI	Ecological Condition	UHI Intensity	Interpretation
UTFVI < 0,000	Very Good	None	Ecologically stable
0,000 ≤ UTFVI < 0,005	Good	Weak	Healthy environment
0,005 ≤ UTFVI < 0,010	Normal	Moderate	Mild heat stress
0,010 ≤ UTFVI < 0,015	Poor	Strong	Significant heat stress
0,015 ≤ UTFVI < 0,020	Very Poor	Very Strong	Severe heat stress
UTFVI ≥ 0,020	Extremely Poor	Extremely Strong	Critical heat stress

Source: thresholds adopted from (Hadibasyir et al., 2020)

Table 4. NDBI Classification. Increased NDBI Values Reflect Higher Built-Up Density, Typically Correlating with Higher Urban Surface Temperatures

NDBI Value	Classification
NDBI < 0	Non-Built-up
0 ≤ NDBI < 0,050	Low Density
0,050 ≤ NDBI < 0,097	Moderate Density
NDBI ≥ 0,097	High Density

Source: modified from (Isnaeni and Prasetyo, 2021).

2.3.2. Surface Temperature and Energy Balance

LST was derived from radiometrically and atmospherically corrected Landsat 9 thermal bands. UTFVI was then applied to evaluate ecological conditions, as it reflects the deviation of surface thermal characteristics from the mean city temperature (Isnaeni and Prasetyo, 2021; Sameh et al., 2022; Sholihah et al., 2023). While UTFVI is conventionally calculated using the mean LST of the respective study area, this study used the combined mean LST of Jakarta and Semarang City as a common reference to enable direct comparison of thermal conditions between the two cities. Using separate city-specific means would independently normalize LST within each city, making the resulting UTFVI values less comparable across cities. The combined mean therefore provides a consistent thermal baseline for both cities and allows differences in their relative thermal conditions to be assessed within the same reference framework. Accordingly, UTFVI values represent relative thermal conditions within the two-city study domain rather than city-specific thermal anomalies. UTFVI is generally computed as:

$$UTFVI = \frac{T_s - T_{smean}}{T_{smean}} \quad (8)$$

where T_s is the surface temperature of a pixel (K) and T_{smean} is the mean surface temperature of the entire city (K). High values of LST and UTFVI indicate thermal stress and poorer ecological quality, whereas lower values reflect relatively cooler areas with better ecological conditions (Table 5).

Estimation of surface energy balance terms was based on the SEBAL algorithm. Albedo (α) was derived from reflectance spectra, continue with net radiation (R_n) which is the difference between incoming short wave radiation (R_{sIn}) and outgoing shortwave radiation (R_{sOut}) and outgoing long wave radiation (R_{lOut}). Soil heat flux (G) was determined as a fraction of net radiation, whereas sensible heat flux (H) was estimated by means of the Bowen ratio method. Latent heat flux (LE) was determined as the residual of the energy balance (Bastiaanssen, 2000; 1294

Wiweka, 2014). The general form of the energy balance equation is expressed as (Artikanur & June, 2019):

$$R_n = G + H + LE \quad (9)$$

2.3.3. Land Surface Temperature Validation

Due to limited access to in-situ thermal data, validation of Landsat-derived LST followed the approach of previous study, focusing on spatial pattern comparison (Ali et al., 2017). MODIS MOD11A2.061 was used as reference because of its ability to cover the study areas consistently. Landsat LST was resampled from 100 m to 1000 m using bilinear interpolation to match MODIS resolution. The agreement between datasets was evaluated using the Pearson correlation coefficient (r), confirming the reliability of Landsat data for urban thermal analysis.

2.3.4. Statistical Analysis

The relationships among UTFVI, NDVI, and NDBI were analyzed using simple and multiple linear regression, with UTFVI as the dependent variable, NDVI as an ecological indicator, and NDBI as a proxy for urbanization (Isnaeni and Prasetyo, 2021). Prior to multiple regression, multicollinearity was tested using the VIF to ensure predictor independence (Sholihah et al., 2023).

Differences between Jakarta and Semarang City were evaluated utilising the Mann-Whitney U test, a non-parametric technique appropriate for spatially heterogeneous data and unequal sample sizes (Cantica et al., 2023). A corrected significance threshold ($\alpha = 0,007$) was applied to minimize Type I error (Emerson, 2020). Topographic variation in Semarang City was not explicitly modeled but handled through the use of averaged multi-scene Landsat imagery and city-wide mean LST in UTFVI calculations, ensuring fair inter-city comparison.

3. RESULTS AND DISCUSSION

3.1. General Characteristic and Land Profile

3.1.1. Supervised Classification

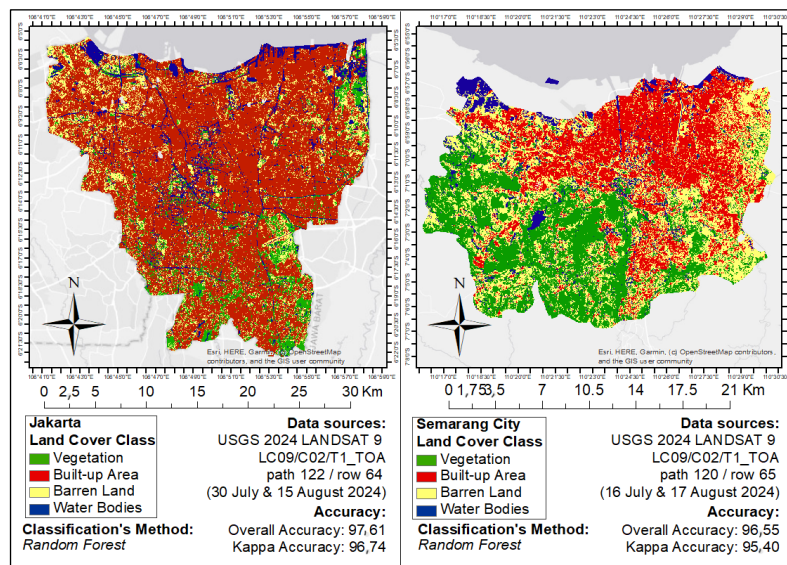
The supervised land cover classification in both regions achieved overall accuracy and kappa values exceeding 95% (Table 6). The accuracy of confusion matrix calculations for remote sensing must be at least 85% to be considered correct (Sampurno and Thoriq 2016). Jakarta's land cover was dominated by built-up areas (64,38%), and spatially, built-up areas are distributed across most parts of the city, while vegetation is observed in smaller and fragmented patches (Figure 3a). On the other hand, vegetated and

open land areas are observed more widely in Semarang City, respectively, in its peripheral zones (Figure 3b). These results align with Wang et al. (2021), who mentions that built-up increment intensity directly reduces vegetation cover and

subsequently enhances urban heat accumulation. Furthermore, the percentage distribution of land cover classes (Figure 4) suggests distinct differences between Jakarta and Semarang City, particularly in the proportion of built-up and vegetated area.

Table 6. Accuracy Test Values for Land Cover Classification in Both Study Areas

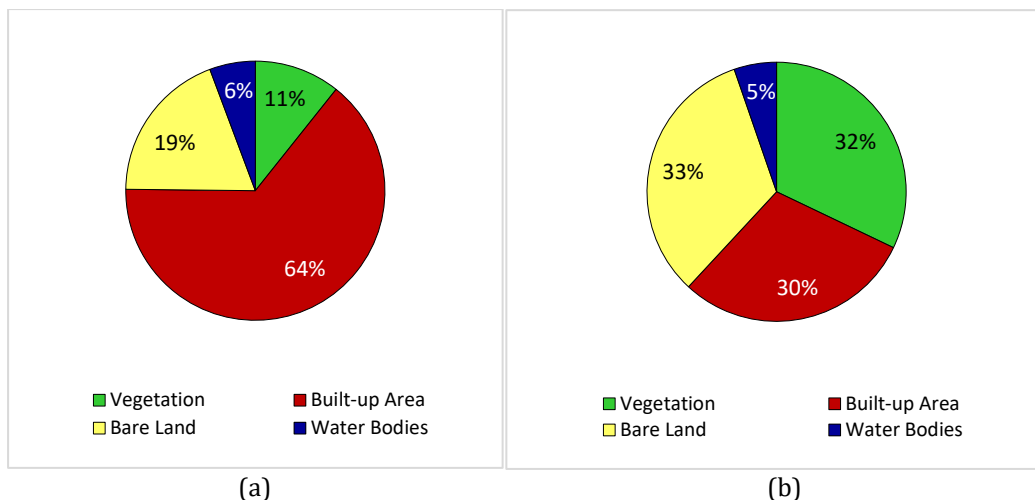
Jakarta					
Sample (Training/Testing)	Class	Producer's Accuracy (%)	User's Accuracy (%)	Overall Accuracy (%)	Kappa Statistic
160/40	Water Body	100	100	97,61	0,9674
	Vegetation	100	87,5		
	Bare Soil	91,67	100		
	Built-up	100	100		
Semarang City					
Sample (Training/Testing)	Class	Producer's Accuracy	User's Accuracy	Overall Accuracy (%)	Kappa Statistic
124/31	Water Body	100	100	96,55	0,954
	Vegetation	100	100		
	Bare Soil	100	87,5		
	Built-up	85,71	100		



(a)

(b)

Figure 3. Supervised Land Cover Classification Results for (a) Jakarta and (b) Semarang City using the Random Forest Algorithm based on Landsat 9 Imagery (2024)



(a)

(b)

Figure 4. Percentage Distribution of Land Cover Classes in (a) Jakarta and (b) Semarang City Derived from Landsat 9 Imagery (2024). Jakarta is Dominated by Built-Up Areas, Whereas Semarang City Shows a Higher Proportion of Vegetation and Open Land, Indicating Differences in Urbanization Intensity

Vegetated areas that are relatively larger in Semarang City could work as ecological buffers that lower temperature stress and maintain local environmental balance. However, if the city continues its urban growth without adequate preparation, especially to maintain effective conservation of its vegetated areas, it can lead to ecological degradation similar to that of Jakarta.

Another key point to consider is that extreme thermal environments caused by UHI can become a limiting factor for vegetation in tropical urban areas, which significantly affects both photosynthesis and transpiration processes (Kabano et al., 2021; Wang et al., 2021). In this context, it is quite concerning that Indonesia, as a developing tropical country, could become more vulnerable to challenges arising from uncontrolled urbanization and limited ecological management capacity.

3.1.2. Land Surface Temperature Validation

Figures 5a and 5b present correlation results of LST patterns from Landsat 9, which were resampled to a 1 km resolution to match the MODIS imagery. The estimated LST values from Landsat 9 ranged between

23–31 °C, while MODIS LST products ranged between 30–37 °C. The observed distinction in surface temperature ranges is likely to be a natural consequence of differences in sensor characteristics, retrieval algorithms, and acquisition times. Also, the MODIS imagery used in this study was composited from two 8-day scenes, whereas Landsat 9 utilized two single-date scenes.

A similar deviation has been reported in a previous study, which emphasized that emissivity assumptions and sensor-specific calibration can lead to significant temperature differences (Simó et al., 2016). However, the study prioritized spatial pattern consistency rather than absolute temperature agreement, as the objective was to validate the spatial distribution of surface temperature rather than its temporal variability.

Despite these differences, Figure 6 and Figure 7 show that the land surface temperature patterns obtained from Landsat 9 and MODIS were generally consistent. The Pearson correlation coefficient was 0,71 for Jakarta and 0,93 for Semarang City, classified as strong and very strong correlations, respectively (Sugiyono, 2012).

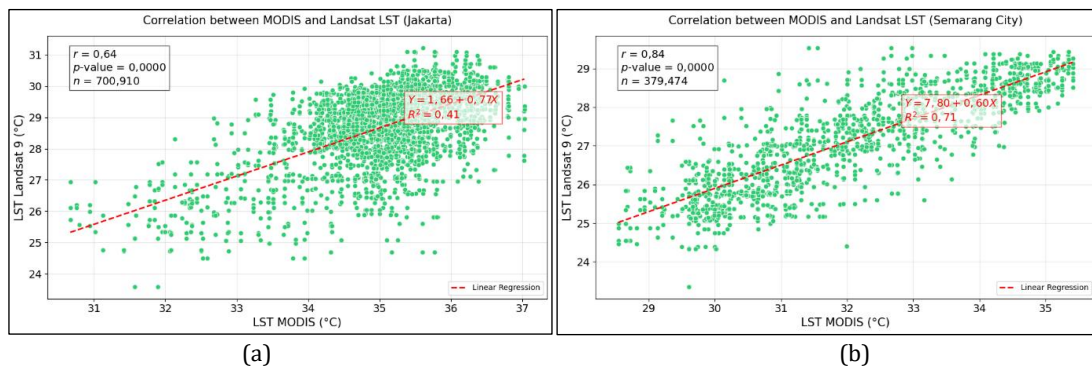


Figure 5. Correlation Between MODIS LST (MOD11A2) and Landsat 9-Derived Land Surface Temperature (LST) for (a) Jakarta and (b) Semarang City. Landsat Data Were Resampled to 1 km Resolution to Match MODIS, Highlighting the Consistency of Spatial Temperature Patterns Between Sensors

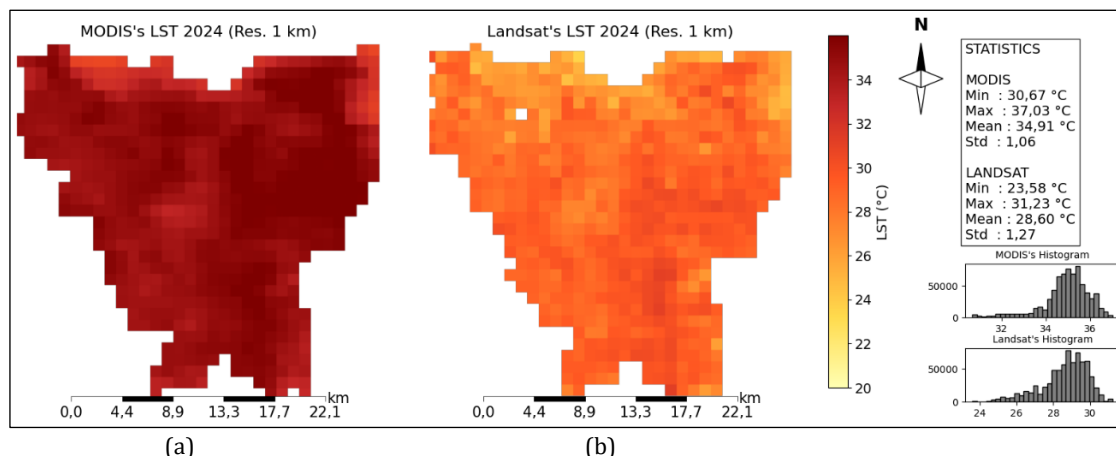


Figure 6. Spatial Distribution of Land Surface Temperature (LST, °C) Derived from (a) MODIS MOD11A2 and (b) Landsat 9 (Resampled to 1 km) in Jakarta (2024). Despite Differences in Absolute Temperature Values, Both Datasets Exhibit Similar Spatial Distribution of Thermal Hotspots

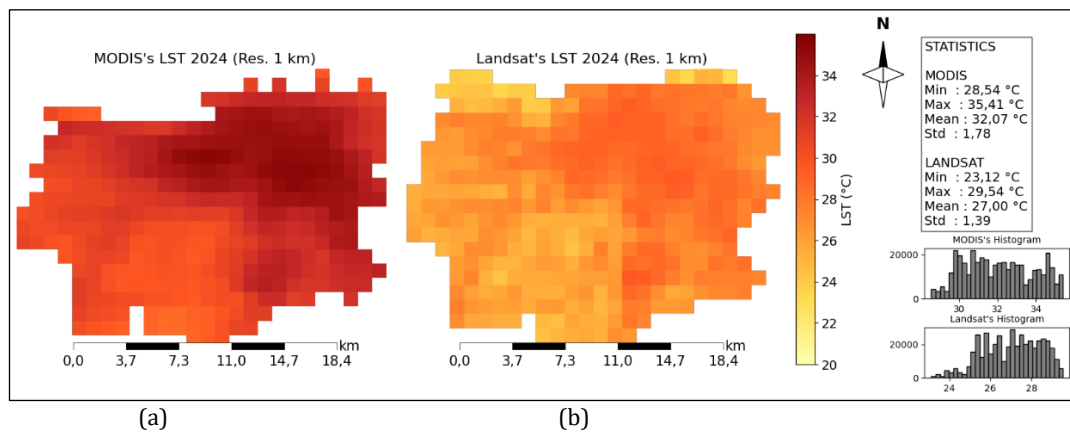


Figure 7. Spatial Distribution of Land Surface Temperature (LST, °C) Derived from (a) MODIS MOD11A2 and (b) Landsat 9 (Resampled to 1 km) in Semarang City (2024)

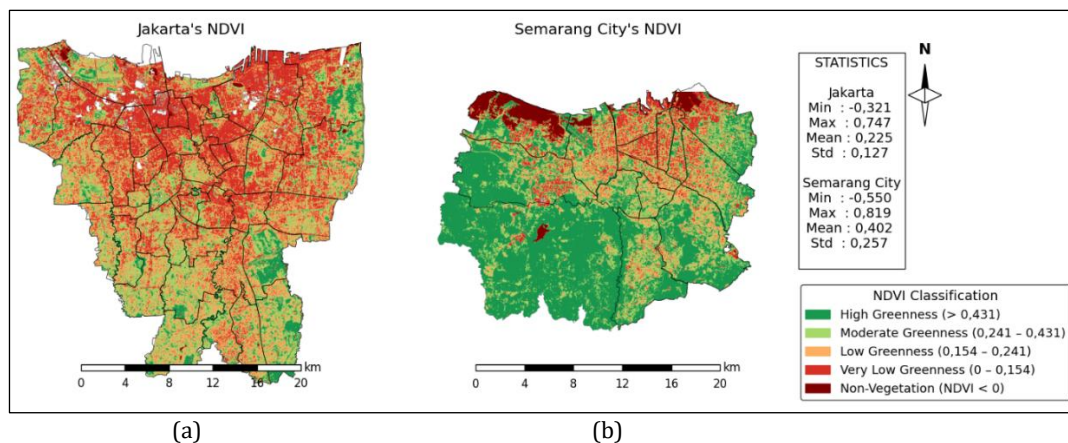


Figure 8. Spatial Distribution of NDVI in (a) Jakarta and (b) Semarang City Derived from Landsat 9 Imagery (2024). Higher NDVI Values in Semarang City Reflect Denser Vegetation Cover, while Jakarta Exhibits Limited and Fragmented Green Areas

3.2. Impact differences of urbanization scale on ecological condition

3.2.1. Spatial Patterns of Surface and Ecological Indicators

The differences in urbanization scale between Jakarta and Semarang City provide an important context for interpreting their surface characteristics. Jakarta covers a larger administrative area and has a substantially larger population, with more than 10 million residents across approximately 662 km², compared with approximately 1.6 million residents across 374 km² in Semarang City. Jakarta also has a considerably higher population density (14,555 people/km²) than Semarang City (4,425 people/km²), indicating a more intensive urban context. These differences in urban scale and population density are reflected in the contrasting proportions and spatial distribution of built-up and vegetated surfaces between the two cities.

As shown in Figure 8 and Figure 9, respectively, NDVI and NDBI ranges in Jakarta (-0.32 to 0.75; -0.65 to 0.40) were narrower than those in Semarang City (-0.55 to 0.82; -0.99 to 0.46). Jakarta had a lower mean NDVI (0.225) and a higher mean NDBI (-0.046) than Semarang City (0.402 and -0.180, respectively), indicating greater vegetation cover and less

pronounced built-up characteristics in Semarang City. Additionally, the Mann-Whitney U test (Table 7) confirmed that Jakarta had significantly lower NDVI and higher NDBI values ($p < 0.007$), with effect sizes of $r = -0.416$ for NDVI and $r = 0.378$ for NDBI. These results confirm clear differences in vegetation and built-up surface characteristics between Jakarta and Semarang City.

The spatial distribution of these indices further shows contrasting landscape patterns between the two cities. As shown in Figure 8, vegetation in Jakarta was generally distributed as small and fragmented patches across the urban area, whereas Semarang City exhibited more extensive vegetation, particularly in the southern and western parts of the city. Conversely, Figure 9 shows that high NDBI values were more extensive and spatially widespread across Jakarta, while in Semarang City, higher built-up intensity was more concentrated around the main urbanized areas. Thus, the two cities differed not only in the magnitude of vegetation and built-up characteristics but also in their spatial arrangement, with Jakarta showing a more extensive built-up pattern interspersed with fragmented vegetation, while Semarang City showed more extensive vegetated areas and more concentrated built-up surfaces.

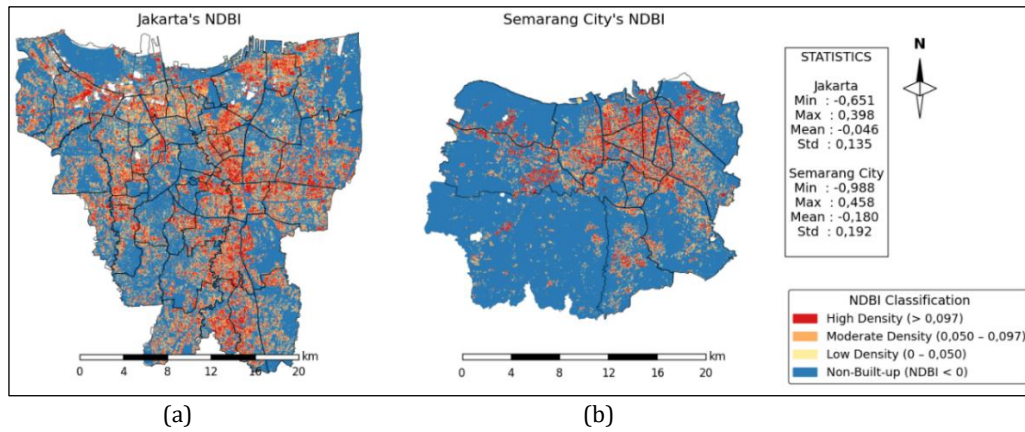


Figure 9. Spatial Distribution of NDBI in (a) Jakarta and (b) Semarang City Derived from Landsat 9 imagery (2024). Jakarta Shows Higher Built-Up Intensity, Indicating More Extensive Impervious Surfaces Compared to Semarang City

Table 7. Results of the Mann–Whitney U Test Comparing Environmental Variables Between Jakarta (U1) and Semarang City (U2). All Variables Show Statistically Significant Differences ($p < \text{adjusted } \alpha$). Mean Rank Values Indicate that Jakarta has Higher UTFVI and NDBI, while Semarang City has Higher NDVI

Variable	U1	U2	Z	P-value	Adjusted α (Bonferroni)	Effect Size (r)	r	Jakarta's Mean Rank	Semarang City's Mean Rank
UTFVI	678	42	5,214	< 0,001	0,007	0,668	0,67	38,07	11,13
NDVI	162	558	-3,25	0,001	0,007	-0,416	0,42	26,6	43,38
NDBI	540	180	2,951	0,003	0,007	0,378	0,38	35	19,75

A two-tailed Mann–Whitney U test was conducted with Bonferroni correction for multiple comparisons (adjusted $\alpha = 0,007$). Effect size (r) was calculated using the standardized Z statistic: $r = Z / \sqrt{N}$. Direction of difference was interpreted based on mean rank comparisons between groups.

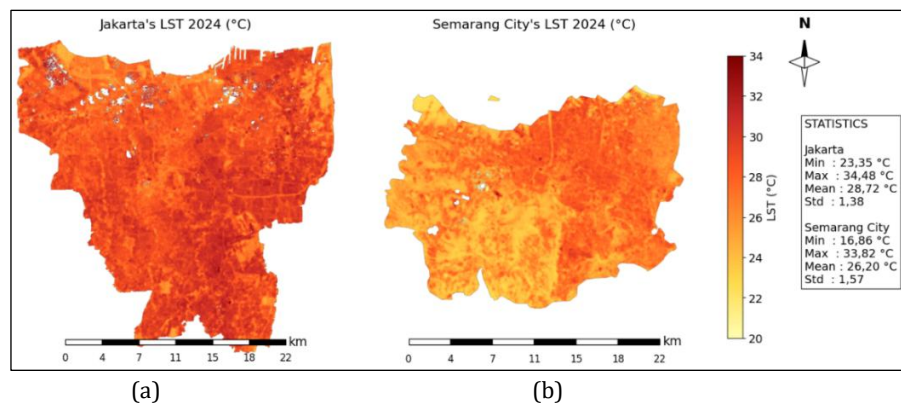


Figure 10. Spatial Distribution of Land Surface Temperature (LST) in (a) Jakarta and (b) Semarang City during July–August 2024, Showing Higher Temperatures in Built-Up Areas and Lower Values in Vegetated Regions

The differences in surface characteristics and their spatial arrangement were also reflected in the LST distribution (Figure 10). Jakarta exhibited higher surface temperatures over broader areas, particularly in locations dominated by built-up surfaces, whereas Semarang City showed relatively lower temperatures across its larger vegetated areas. In Semarang City, higher-temperature areas were more concentrated around the main built-up zones, while the southern and western vegetated areas generally exhibited lower LST values. Thus, the spatial distribution of surface temperature broadly corresponded to the observed arrangement of built-up and vegetated surfaces in both cities.

A similar spatial pattern was observed in the UTFVI distribution (Figure 11). Based on the UTFVI formulation, lower T_s values relative to T_{smean} result in lower UTFVI values, indicating relatively cooler thermal conditions, whereas higher T_s values relative

to T_{smean} result in higher UTFVI values, indicating relatively warmer thermal conditions. In this study, UTFVI values were interpreted relative to the average mean LST of Jakarta and Semarang City. Therefore, the index indicates whether a location is relatively cooler or warmer than the thermal baseline of the two-city study domain, rather than indicating the thermal anomaly of each city independently. Under this common reference, the higher and more concentrated LST values in Jakarta resulted in a greater proportion of areas with relatively higher UTFVI values, whereas the lower LST values and greater vegetation coverage in Semarang City were associated with relatively cooler thermal conditions (Figure 11). As summarized in Table 8, Semarang City exhibited better relative ecological conditions, with 74.68% of its area classified as very good, compared with 17.95% in Jakarta.

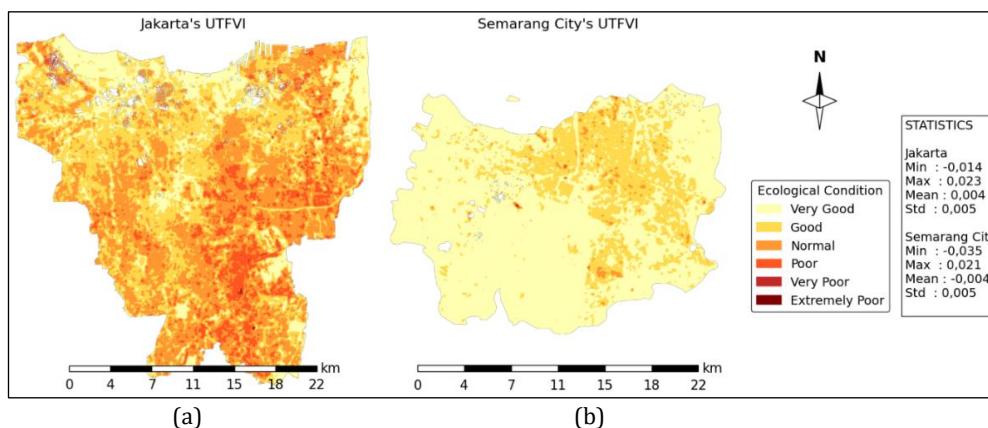


Figure 11. Spatial Patterns of the Urban Thermal Field Variance Index (UTFVI) in (a) Jakarta and (b) Semarang City during July–August 2024, Showing Higher Temperatures in Built-Up Areas and Lower Values in Vegetated Regions

Table 8. Comparative Ecological Quality Based on UTFVI Values for Jakarta and Semarang City

Category	Jakarta		Semarang City (%)	
	Percentage (%)	Total of Pixels (n)	Percentage (%)	Total of Pixels (n)
Very good	17,95	125011	74,68	299897
Good	34,8	242433	23,79	95541
Normal	38,89	270912	1,48	5934
Poor	8,28	57646	0,05	194
Very poor	0,08	536	0,01	25
Extremely poor	< 0,01	48	< 0,01	5
Total	100	696586	100	401596

These findings are supported by other studies, which also mentioned that high UTFVI values indicate significant thermal environmental degradation and are often associated with areas of low vegetation and dense built-up structures (Hadibasyir et al., 2020; Sameh et al., 2022). Denser built-up areas in Jakarta potentially decrease their ecological resilience, which shows how intensified urban development directly amplifies thermal stress and environmental vulnerability. This condition also makes cities more sensitive to worsening environmental pressures, as elevated temperatures and dense urban configurations can influence atmospheric processes related to urban air quality (Wangintan et al., 2024). For Semarang City, the better ecological quality suggests that mid-sized cities still possess opportunities to integrate sustainable planning before UHI effects intensify. This demonstrates the importance of proactive governance: ecological health declines disproportionately once urban density surpasses a critical threshold.

3.2.2. Statistical Analysis

The results of a simple linear regression analysis (Table 9) show that both vegetation (NDVI) and built-up area (NDBI) are significant predictors of the ecological condition index (UTFVI) in Jakarta and Semarang (p -value < 0,001). It also shows that increasing vegetation density is negatively correlated with UTFVI, while increasing built-up area density is positively correlated. Comparatively, NDBI explains more variation in UTFVI (R^2 NDBI > R^2 NDVI) in both

cities. The NDVI in Semarang City has a slightly stronger correlation and contribution (Semarang City; r -0,580 and R^2 0,345) than the NDVI in Jakarta (Jakarta; r -0,548 and R^2 0,301). This indicates that vegetation in Semarang City has a stronger and more consistent effect on reducing surface heat than in Jakarta. On the other hand, the multiple regression results (p -value < 0,001; Table 10) show that NDBI contributes positively to the increase in UTFVI, with a higher coefficient in Jakarta (0,0225) than in Semarang City (0,0210). Conversely, NDVI contributes negatively, with a stronger effect in Semarang City (-0,0020) than in Jakarta (-0,0012). This finding confirms that the presence of buildings is more dominant in influencing thermal ecological conditions than vegetation, especially in megapolitan areas. Overall, the combination of NDVI and NDBI explains 55,3% of the variation in UTFVI in Jakarta and 57,3% in Semarang.

The results of both simple and multiple linear regression tests indicate that multiple urbanization worsens thermal ecological conditions more than vegetation mitigates them. These results match as well with previous studies, such as Zhao et al.'s (2020) study on the thermal contribution of land cover types in Beijing, which showed that the presence of buildings is indeed stronger in increasing temperatures than the presence of vegetation in reducing temperatures. Improving the quality of urban ecological conditions can be achieved by increasing vegetation and reducing the density of built-up areas (Hadibasyir and Firdaus 2022).

Table 9. Results of Simple Linear Regression and Pearson Correlation Analysis of NDVI and NDBI in Relation to UTFVI in Jakarta and Semarang City. R Values and Regression Coefficients Indicate a stronger Positive Association Between Built-Up Density and Ecological Stress than Vegetation Density in Both Cities

Jakarta							
Variables	Model's Equation	Std. Error	P-value (t-test)	R ²	Sample Size (n)	F-statistic ^b	R (pearson)
NDVI	UTFVI = 0,0054 – 0,0124(NDVI) ^a	2,87 × 10 ⁻⁵	< 0,001	0,3	434.023	1,87 × 10 ⁵ , p < 0,001	-0,548
NDBI	UTFVI = 0,0020 + 0,0239(NDBI) ^a	3,22 × 10 ⁻⁵	< 0,001	0,55		5,34 × 10 ⁵ , p < 0,001	0,743
Semarang City							
Variables	Model's Equation	Std. Error	P-value (t-test)	R ²	Sample Size (n)	F-statistic ^b	R (pearson)
NDVI	UTFVI = 0,0061–0,0139(NDVI) ^a	3,1 × 10 ⁻⁵	< 0,001	0,35	396.069	2,01 × 10 ⁵ , p < 0,001	-0,58
NDBI	UTFVI = 0,0034 + 0,0228(NDBI) ^a	3,15 × 10 ⁻⁵	< 0,001	0,57		5,24 × 10 ⁵ , p < 0,001	0,755

^aAll regression coefficients are statistically significant based on t-tests (p-value < 0,05; $\alpha = 0,05$). ^bAll regression models are statistically significant based on F-tests (p-value < 0,05; $\alpha = 0,05$).

Table 10. Multiple Regression Results of NDVI and NDBI on UTFVI, Highlighting Dominant Built-Up Effects in Jakarta and Vegetation Cooling in Semarang

Vegetation Mapping in Semarang						
Jakarta						
Variable	Coefficient	Std. Error	P-value (t-test)	R ²	Sample Size (n)	F-statistic ^b
Constant	0,0024 ^a	1,15 × 10 ⁻⁵	< 0,001	0,55	434.023	2,68 × 10 ⁵ , p < 0,001
NDVI ^c	-0,0012 ^a	3,23 × 10 ⁻⁵	< 0,001			
NDBI ^c	0,0225 ^a	4,56 × 10 ⁻⁵	< 0,001			
Semarang City						
Variable	Coefficient	Std. Error	P-value (t-test)	R ²	Sample Size (n)	F-statistic ^b
Constant	0,0040 ^a	1,28 × 10 ⁻⁵	< 0,001	0,57	396.069	2,66 × 10 ⁵ , p < 0,001
NDVI ^c	-0,0020 ^a	3,55 × 10 ⁻⁵	< 0,001			
NDBI ^c	0,0210 ^a	4,48 × 10 ⁻⁵	< 0,001			

^aAll regression coefficients are statistically significant based on t-tests (p < 0,05; $\alpha = 0,05$). ^bAll regression models are statistically significant based on F-tests (p < 0,05; $\alpha = 0,05$). ^cNDVI and NDBI were tested for multicollinearity (Jakarta's VIF = 1,59; Semarang's VIF = 3,12).

Table 11. Results of the Mann-Whitney Difference Test of Energy Balance Components Between Jakarta (U1) and Semarang City (U2). Significant Differences (p < adjusted α) are Observed Across all Components (Rn, G, H, and LE), Indicating Distinct Surface Energy Exchange Patterns Between the Two Study Areas. Mean Rank Values Suggest Jakarta has Higher Rn, G, and H, while Semarang City has Higher LE

Variable	U1	U2	Z	P-value	Adjusted α (Bonferroni)	Effect Size (r)	r	Jakarta's Mean Rank	Semarang City's Mean Rank
Rn	529	191	2,771	0,003	0,007	0,355	0,355	34,76	20,44
G	720	0	5,902	< 0,001	0,007	0,756	0,756	39	8,5
H	715	5	5,82	< 0,001	0,007	0,745	0,745	38,89	8,81
LE	47	673	-5,132	< 0,001	0,007	-0,657	0,657	24,04	50,56

A two-tailed Mann-Whitney U test was conducted with Bonferroni correction for multiple comparisons (adjusted $\alpha = 0,007$). Effect size (r) was calculated using the standardized Z statistic: $r = Z / \sqrt{N}$. Direction of difference was interpreted based on mean rank comparisons between groups.

3.3. Comparative Analysis of Surface Energy Balance Components

The Mann-Whitney U test (Table 11) indicates significant differences in all surface energy balance components between Jakarta and Semarang City, reflecting contrasting patterns of energy partitioning. As shown in Figure 12, Jakarta exhibited a stronger dominance of sensible heat flux ($H = 141,41 \text{ W/m}^2$), whereas Semarang City had substantially higher latent heat flux ($LE = 142,91 \text{ W/m}^2$), despite comparable mean net radiation (Rn) of $236,41 \text{ W/m}^2$ and $235,64 \text{ W/m}^2$, respectively. Ground heat flux was also slightly higher in Jakarta ($G = 32,13 \text{ W/m}^2$) than in Semarang City ($G = 28,26 \text{ W/m}^2$). These differences are consistent with their contrasting surface composition and spatial distribution, with built-up areas accounting for 64,38% of Jakarta and 29,77% of Semarang City, while vegetation accounted for

10,73% and 32,08%, respectively. Thus, the greater extent of built-up surfaces in Jakarta favored sensible heat transfer at the city scale, whereas the more extensive vegetation in Semarang supported greater latent heat flux. The spatial concentration of built-up areas in Semarang, however, still produced localized areas of higher sensible heat flux and surface temperature. This pattern is consistent with the physical characteristics of urban surfaces, as impervious materials can absorb and store heat and contribute to sensible heat transfer (Heisler and Brazel, 2010; Kara et al., 2025).

Energy partitioning should also be considered in relation to surface albedo as well. Albedo varies among urban materials depends on its composition and condition; for example, fresh asphalt generally has lower reflectivity than aged asphalt, then brighter surfaces such as concrete has higher albedo (Tsoka et

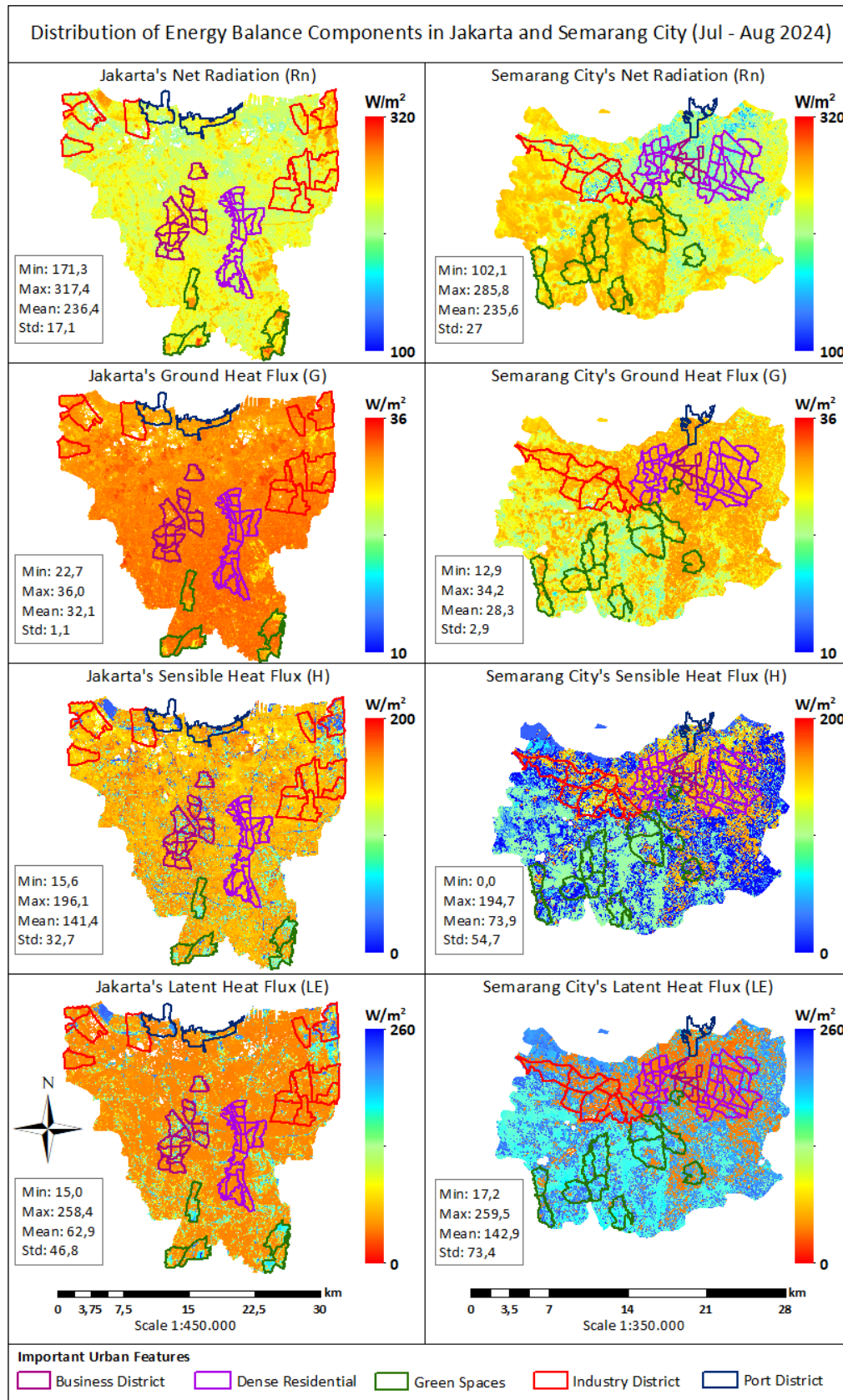
al., 2026). Common urban materials such as concrete, asphalt, and bricks generally exhibit relatively low albedo and high thermal admittance, increasing their capacity for heat absorption and storage (Heisler and Brazel, 2010; Ihsan et al., 2022). Although high-albedo roofing materials (≥ 0.65) have been recommended as a mitigation strategy for reducing urban heat (Sari et al., 2024; Wai et al., 2025), both Jakarta and Semarang City contain extensive built-up surfaces with relatively low albedo (Figure 13). Surfaces with an albedo of approximately 0.2–0.3 reflect only about 20–30% of incoming shortwave radiation. The remaining energy is absorbed by the surface and partitioned into sensible heat (H), latent heat (LE), and ground heat flux (G), depending on surface properties, moisture availability, and vegetation cover. Thus, albedo primarily regulates the amount of shortwave energy entering the surface energy balance, while surface characteristics influence how that energy is subsequently partitioned.

The spatial distribution of albedo in Figure 14 further illustrates this interaction at the local scale. The figure is not intended as a direct comparison between Jakarta and Semarang City, but as a spatial example of the relationships among R_n , G, H, LE, albedo, and LST within Semarang City. The darkest albedo areas in Figure 14e correspond to densely vegetated surfaces, which absorb a relatively large fraction of incoming shortwave radiation and consequently exhibit higher R_n (Figure 14a). However, these areas still show lower LST than some residential areas with relatively higher albedo (Figure 14f). This apparent contrast highlights the different thermal behaviour of vegetated and urban surfaces. Despite absorbing substantial amounts of shortwave radiation, densely vegetated surfaces can dissipate much of the available energy through latent heat flux (LE) associated with evapotranspiration, thereby limiting sensible heating (Figure 14c–d). In contrast, urban materials with limited moisture availability

have less capacity for evaporative cooling and can retain and store absorbed energy within the surface, which is subsequently released through longwave radiation and convective heat transfer (Tsoka et al., 2026; Qian et al., 2023; Pan et al., 2023). Therefore, surfaces with lower albedo do not necessarily exhibit higher LST, as the thermal response depends not only on the amount of radiation absorbed but also on how the absorbed energy is partitioned and released.

This finding highlights the importance of localized surface characteristics in urban heat mitigation. Albedo alone does not determine surface temperature. Its thermal effect depends on the type and condition of the underlying surface, including vegetation characteristics and moisture availability. Therefore, mitigation strategies should consider the local combination of surface reflectivity, material properties, vegetation, and evaporative cooling capacity.

The observed analysis should also be interpreted within the different physical settings of the two cities. Although Jakarta and Semarang City are both located in the northern part of Java Island, their local physical characteristics differ. Jakarta is predominantly flat and low-lying, whereas Semarang City has a north–south topographic gradient from coastal lowlands to hilly areas in the south. This physical heterogeneity may influence local moisture conditions, vegetation distribution, surface exposure, and thermal characteristics, and may interact with the effects of urban development. Thus, while the contrasting vegetation and built-up characteristics provide an important explanation for the differences in energy partitioning, other physical factors may also contribute to the observed spatial variability. As topography was not explicitly incorporated into the present analysis, its independent contribution to the observed differences cannot be quantified and should be considered a limitation of the study.



(a) (b)

Figure 12. Surface Energy Balance Components Map Jakarta and Semarang City, respectively. The Maps Illustrate Differences in Net Radiation (Rn), Sensible Heat Flux (H), Ground Heat Flux (G), and Latent Heat Flux (LE), Reflecting Contrasting Surface Energy Exchange Mechanisms

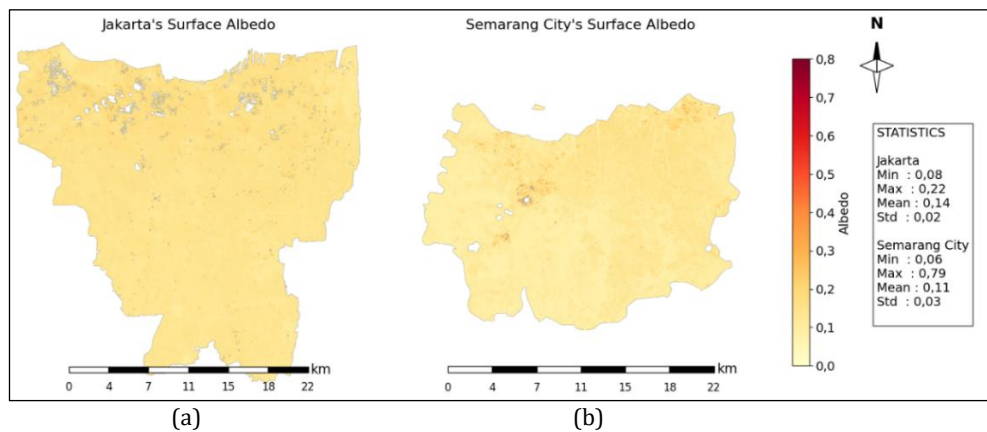


Figure 13. Surface Albedo of (a) Jakarta and (b) Semarang City. Both Cities are Dominated by Low-Albedo Built-Up Surfaces, which Contribute to Higher Heat Absorption and Surface Warming

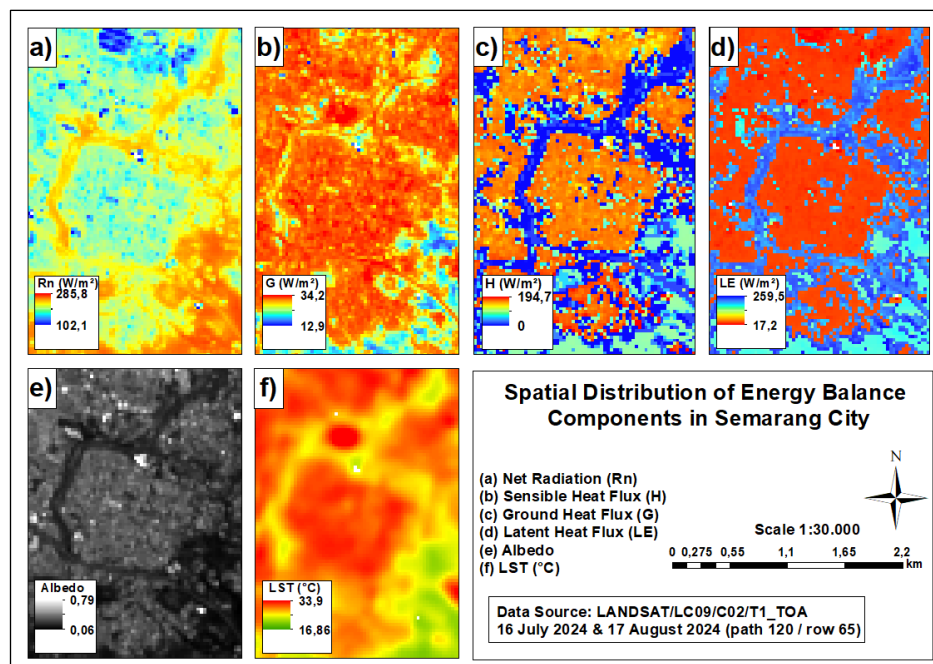


Figure 14. Details of Energy Balance Components (a-d), (e) Albedo, (f) LST, in Semarang City. Vegetated and Less Urbanized Areas Exhibit Higher LE and Lower H, Indicating Efficient Energy Dissipation Through Evapotranspiration. In Contrast, Densely Built-Up Areas are Characterized by Lower Albedo, Higher Sensible Heat Flux, and Elevated Surface Temperatures, Reflecting Greater Heat Storage and Reduced Cooling Capacity

3.4. Limitation

Several limitations should be considered when interpreting the results. First, surface temperature validation was conducted through comparison with MODIS imagery rather than direct field measurements. Differences in spatial resolution, image acquisition dates, and observation frequency may introduce discrepancies between the datasets and may not fully capture temporal variability. Nevertheless, the consistency observed between Landsat 9 and MODIS provides supporting evidence for the reliability of the derived spatial LST patterns.

Second, the estimation of surface energy balance components did not include the incoming longwave radiation due to data limitations and was assumed to be constant or relatively small under clear conditions. This could slightly lead to underestimates of the energy balance components.

Third, topographic heterogeneity represents an additional physical factor that may contribute to the observed spatial variation in surface temperature and energy partitioning, particularly in Semarang City, which has a distinct gradient from low-lying coastal areas in the north to hilly terrain in the south. However, topography was not explicitly incorporated into the present analysis because the primary focus was on the relationships between urban surface characteristics, represented by NDBI and NDVI, and their associated thermal and energy-balance responses. Although the observed differences in H and LE are consistent with the contrasting built-up and vegetation characteristics of the two cities, the contribution of other local physical factors, particularly topography, could not be quantified separately. Future studies could incorporate elevation and other topographic variables to further examine

their contribution alongside urban surface characteristics.

3.5. Implication for Urban Planning and Mitigation

The contrasting thermal and energy-partitioning characteristics identified in Jakarta and Semarang City provide implications for context-specific urban heat mitigation. In Jakarta, the greater proportion of built-up surfaces, higher NDBI, limited vegetation coverage, and stronger sensible heat flux ($H = 141.41 \text{ W/m}^2$) indicate a surface environment with relatively limited potential for evaporative cooling. Given the high population density and extensive built-up environment, mitigation approaches should not rely solely on the expansion of conventional horizontal green spaces. Instead, interventions that can be integrated into existing built-up areas, such as vertical greening, reflective surface treatments, cool pavements, and measures that improve urban ventilation, may provide relevant options for reducing heat accumulation and enhancing heat dissipation (Hadibasyir et al., 2020; Sari et al., 2024; Wai et al., 2025). These recommendations represent research implications based on the observed surface characteristics and energy-partitioning patterns, rather than direct assessments of the effectiveness of individual mitigation measures.

In Semarang City, the greater vegetation coverage, higher NDVI, and substantially higher latent heat flux ($LE = 142.91 \text{ W/m}^2$) indicate a greater contribution of vegetation-related evaporative cooling to surface energy partitioning at the city scale. However, the spatial concentration of built-up surfaces in the main urbanized areas was also associated with higher H and LST, indicating that localized thermal hotspots remain present despite the greater overall vegetation coverage. The findings therefore highlight the importance of maintaining existing vegetated areas as urban development continues, particularly in areas with substantial vegetation coverage such as Gunungpati and Mijen. Integrating indicators such as NDVI and UTFVI into spatial planning could support the identification of areas where vegetation contributes to thermal regulation and where changes in vegetation cover may be accompanied by increasing thermal stress (Darlina et al., 2018; Kumar et al., 2024). Maintaining consistency between the Rencana Tata Ruang Wilayah (RTRW) and actual development is also relevant for preserving existing vegetated areas and their associated cooling functions. However, because the present study did not quantify vegetation cooling distance or evaluate specific planning interventions, further research is needed to determine the spatial extent of vegetation cooling and assess the effectiveness of alternative mitigation strategies under Semarang City's heterogeneous physical setting.

The spatial patterns observed in the energy-balance analysis further suggest that mitigation should consider local surface characteristics rather

than albedo or vegetation cover alone. In Semarang City, for example, densely vegetated areas may exhibit relatively high net radiation while maintaining lower LST because a larger fraction of the absorbed energy can be partitioned into latent heat through evapotranspiration. Conversely, concentrated built-up areas may exhibit higher sensible heat flux and surface temperature. This indicates that the thermal effect of a surface depends on the interaction between surface reflectivity, material properties, vegetation characteristics, and evaporative cooling capacity.

Overall, the findings suggest that urban heat mitigation should be adapted to the characteristics of the urbanization context rather than applied uniformly across cities. In highly built-up environments such as Jakarta, mitigation may need to emphasize interventions that can be integrated within the existing urban fabric, whereas in Semarang City, maintaining extensive vegetated areas while addressing thermal hotspots within concentrated built-up zones may be particularly important. These findings provide directions for spatial planning and future research, while specific mitigation measures require further site-specific assessment.

4. CONCLUSION

Jakarta and Semarang City exhibited contrasting urban thermal patterns corresponding to their different urbanization contexts and surface characteristics. Jakarta's greater extent of built-up surfaces and limited vegetation was associated with more widespread high-temperature areas and higher overall LST and UTFVI, whereas Semarang City, with more extensive vegetated areas, generally exhibited lower temperatures. However, high-temperature areas in Semarang City remained concentrated around its main built-up zones. This contrast indicates that differences between urbanization scales are expressed not only through the overall proportion of built-up and vegetated surfaces, but also through their spatial distribution, resulting in different patterns of surface heat across the two cities.

These contrasting thermal patterns were accompanied by distinct surface energy partitioning despite comparable net radiation. Jakarta's much greater built-up dominance was associated with stronger sensible heat flux ($H = 141.41 \text{ W/m}^2$), while Semarang City, with more extensive vegetation, showed greater latent heat flux ($LE = 142.91 \text{ W/m}^2$). The spatial patterns in Semarang City further demonstrate that higher energy absorption did not necessarily correspond to higher surface temperature: densely vegetated areas with relatively low albedo absorbed substantial incoming radiation but remained cooler because a larger fraction of the available energy was partitioned into latent heat through evapotranspiration. In contrast, built-up areas with slightly higher albedo exhibited higher LST where a greater fraction of available energy was expressed as sensible heat. These findings demonstrate that the impact of urbanization scale is

reflected not only in the extent of built-up and vegetated surfaces, but also in their spatial distribution and associated energy partitioning, which contribute to differences in surface thermal conditions. This indicates that urban heat mitigation should be tailored to the dominant surface characteristics of each urban context, with greater emphasis on reducing sensible heat in highly built-up areas and preserving or enhancing vegetated areas where evaporative cooling can contribute to latent heat flux.

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