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Impacts of Vegetation Dynamics on Land Surface Temperature and Moisture in Kendari City, Indonesia: A Remote Sensing Study

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ABSTRACT

Vegetation is critical in regulating microclimate characteristics such as surface temperature and soil moisture in urban settings. This study used multi-temporal Landsat 8 OLI data from 2014 to 2024 to investigate the spatiotemporal dynamics of vegetation and its impact on land surface temperature (LST) and moisture in Kendari City, Southeast Sulawesi. The NDVI, NDMI, and LST indices were used in the investigation, along with correlation and multiple regression analyses. The findings demonstrated a 205.25 ha decline in vegetation area over ten years, especially in the central districts (Kadia, Mandonga, and Wua-Wua), along with an average surface temperature increase of +2.4-2.5℃. A considerable negative association was identified between NDVI and LST ($r = -0.661$), although NDVI and NDMI exhibited a strong positive relationship ($r = 0.908$). A regression study found that NDVI and LST explained 87.29% of the variation in NDMI ($R^2 = 0.873$). These studies indicate that vegetation effectively lowers surface temperature and maintains land moisture. Kendari's urban design should prioritise establishing green corridors, parks, and protected buffer zones in warm regions while retaining existing vegetation in suburban areas to increase urban climate resilience.

1. INTRODUCTION

Rapid urbanisation has changed cityscapes throughout the tropics, resulting in severe ecological and microclimatic consequences. In many developing towns, unregulated urbanisation has resulted in a loss of plant cover, which naturally regulates local temperatures and humidity. The conversion of green spaces into impervious surfaces changes the surface energy balance, increases heat absorption, and raises the danger of Urban Heat Island (UHI) formation [1, 2].

Kendari City, the capital of Southeast Sulawesi Province, is one of Indonesia's fastest-growing coastal cities, with an annual population growth rate of 1.63%, which exceeds the national average of 1.49% [3]. Its importance as a regional economic hub, which supports nickel mining in neighbouring provinces, has hastened land conversion for housing and infrastructure development. The city's hilly terrain and the fact that it is located between the coast and the mountains make it especially vulnerable to environmental damage from more people moving to cities and more business units opening.

Previous research on urban heat and vegetation dynamics has been widely conducted in cities such as Manila [4], Kunming [5], and Mysuru [6], but few studies have focused on Southeast Asian mid-sized cities like Kendari, where the interactions between vegetation, surface temperature, and soil moisture are still poorly understood. Remote sensing provides an excellent way to track these characteristics throughout time [7, 8].

The study's particular objectives are to quantify spatial and temporal changes in NDVI, LST, and NDMI in Kendari City from 2014 to 2024. Analyse the statistical correlations between NDVI, NDMI, and LST. Determine spatial hotspots of thermal stress and make area-specific recommendations for sustainable urban planning.

2. MATERIAL AND METHOD

The study was conducted in Kendari City, Southeast Sulawesi Province, which is located just south of the equator at coordinates 3°54'40" to 4°5'5" South Latitude and 122°26'33" to 122°39'14" East Longitude (Figure 1). This region has a tropical monsoon climate characterised by annual rainfall ranging from 1,700 to 2,500 mm and average temperatures between 23℃ and 32℃. The landscape ranges from coastal plains to rolling hills, which affects both vegetation distribution and temperature gradients.

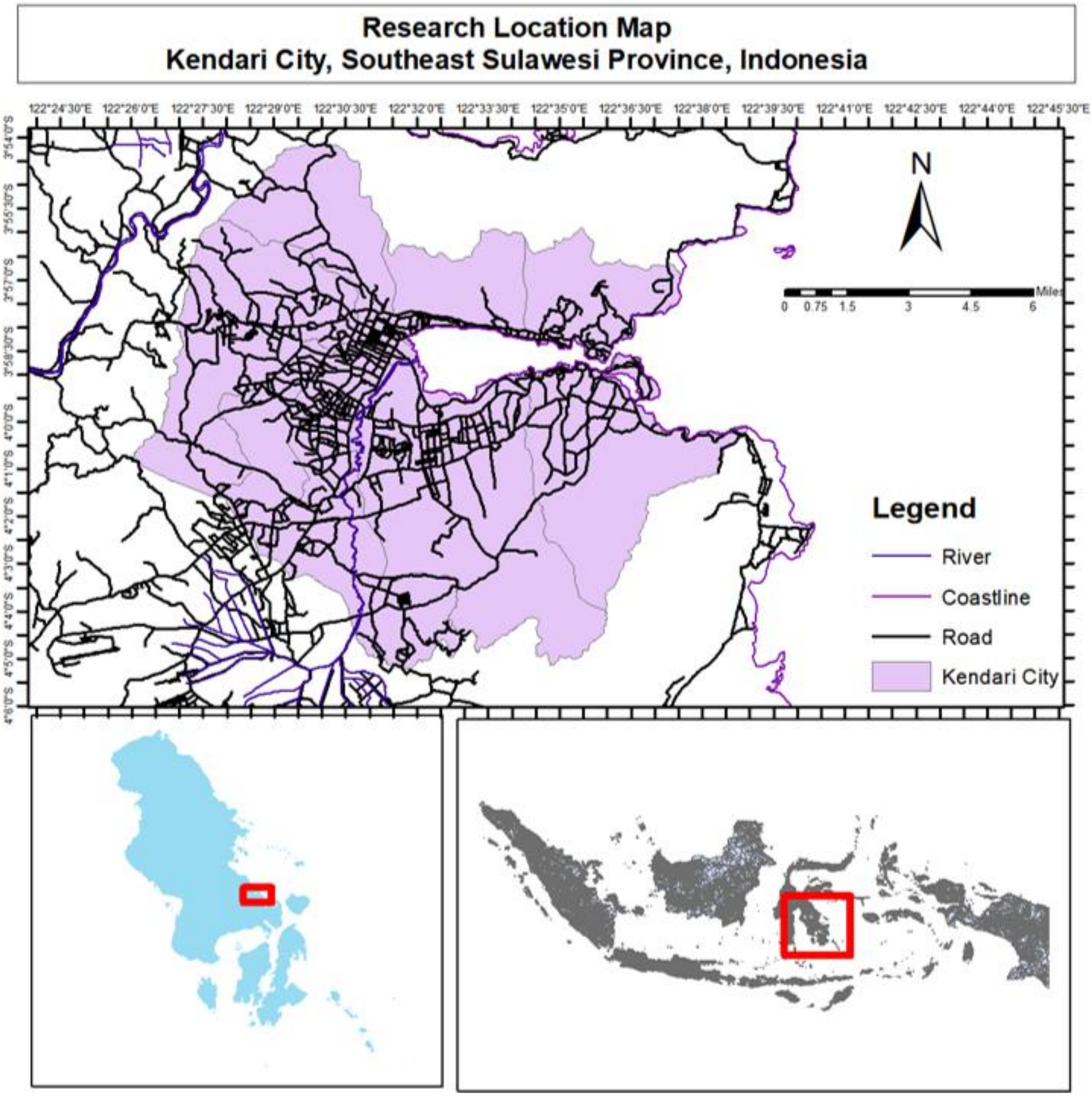

Figure 1. Study site

This research requires the following tools and materials: a global positioning system (GPS), a camera, stationery, Landsat 8 and 9 OLI imagery, a Kendari City administrative map, and climatic data.

2.1 Data and preprocessing

Landsat 8 and 9 OLI/TIRS imagery (path 112, row 63) for 2014 and 2024 were retrieved from the USGS Earth Explorer with negligible cloud cover. The imagery was radiometrically calibrated and atmospherically corrected using the dark object subtraction (DOS) method [9]. Geometric correction was made using the UTM Zone 51S projection.

The land surface temperature (LST) algorithm can be calculated by first converting pixel values in a picture to radians, which are then converted to Kelvin. Kelvin temperature units are converted to Celsius, which is more widely used. The data analysis process employs the land surface temperature algorithm, which is constructed using the temperature brightness technique, as detailed in the following steps.

2.1.1 Converting digital numbers to spectral radians

The first step is to convert the digital numbers on Landsat 8 into spectral radiance using the following equation:

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

where, L_λ: Spectral radiance, M_L: Scale factor, Q_{cal}: Digital number, A_L: Increasing factors.

2.1.2 Converting radiance to brightness temperature (BT)

The Brightness Temperature represents the apparent temperature measured by the satellite sensor, without corrections for land surface emissivity. Spectral radiance was converted to brightness temperature (BT) in Kelvin using Planck's equation.

$$BT = \frac{K_2}{In\left(\frac{K_1}{L_\lambda} + 1\right)} \tag{2}$$

where, BT: Brightness temperature (K), K_1 and K_2: Calibration constants for Landsat 8/9 TIRS thermal band.

2.1.3 Converting Kelvin to Celsius

The BT values were converted to degrees Celsius for interpretation.

$$BT\ (℃) = BT(K) - 273.15 \quad (3)$$

2.1.4 Normalized difference vegetation index (NDVI)

The NDVI is a method for estimating vegetation values. In addition to determining land surface temperature, NDVI can also be used to calculate emissivity in the area under study. The NDVI formula is explained here [10].

$$NDVI = \left[\frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}\right] \quad (4)$$

where, NIR: Near-infrared radiation from pixels, RED: Red light radiation from pixels.

2.1.5 Normalized difference moisture index (NDMI)

The NDMI is used to estimate vegetation moisture content and assess the distribution of vegetation density within the study area. The NDMI formula is explained here [11].

$$NDMI = \left[\frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}}\right] \quad (5)$$

where, SWIR is the shortwave infrared band.

2.1.6 Finding the proportion of vegetation value (PV)

To determine the PV value, the NDVI must be scaled to reduce interference from moist soil conditions and surface energy fluxes. The PV value is derived from the following equation [12].

$$PV = \left[\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}}\right]2 \quad (6)$$

where, $NDVI_{min}$: Lowest NDVI value, $NDVI_{max}$: Highest NDVI value.

2.1.7 Land surface emissivity

Surface emissivity is vital, particularly for lowering mistakes in surface temperature estimation with satellite imaging. Several approaches have been developed for determining surface emissivity from remote sensing data. One simple method for determining surface emissivity is to use the Vegetation Index, which has been processed to yield the PV value using the following equation:

$$\varepsilon = 0.004 * PV + 0.986 \quad (7)$$

where, 0.004 is the average emissivity of vegetation in the dense category, 0.986 is the standard emissivity rating for open land.

2.1.8 Land surface temperature (LST)

After knowing the emissivity value, converting the digital number value to radiance, and converting the Kelvin temperature to Celsius, the LST may be calculated using the following equation:

$$LST = \frac{BT}{1 + \left(\frac{\lambda \times BT}{\rho}\right) In\ (\varepsilon)} \quad (8)$$

where, BT: satellite brightness temperature (°C), λ: radiation wavelength (11.5 µm), ρ: h*c/s (14380 m·K), h: Planck's constant = 6.626×10^{-34} J·s, c: Speed of light = 2.998×10^{8} m/s, s: Boltzmann's constant = 1.38×10^{-23} J/K, ε: Surface emissivity.

2.2 Statistical analysis

Correlation and regression studies were carried out on zonal mean values obtained from administrative districts (Kadia, Mandonga, Wua-Wua, Poasia, Kambu, and others). Pearson's correlation assessed the degree of the link, whereas multiple regression determined the combined effect of NDVI and LST on NDMI.

3. RESULTS AND DISCUSSION

3.1 Normalized difference vegetation index (NDVI)

The NDVI analysis of Kendari City shows the spatial and quantitative trends of plant cover during the last decade (Table 1). As illustrated in Figure 2, in 2014, areas with high greenness levels (dense vegetation) dominated suburban districts, particularly in the city's northern, southern, and southwestern regions, where the terrain ranged from steep to gently sloping. However, by 2024, several of these locations had deteriorated in vegetation quality, falling into the medium- and low-greenness classifications, particularly in the Kadia, Mandonga, and Wua-Wua districts. These center districts evolved from thickly forested zones to more developed areas, owing mostly to urban expansion, residential construction, and infrastructure development spurred by population increase and economic activity.

Table 1. NDVI class

NDVI Class	Area (ha)		Change	
	2014	2024	ha	%
High Greenness level	18,190.53	19,684.26	1,493.73	8.21
Medium Greenness level	3,959.20	2,833.40	-1,125.80	-28.44
Low High Greenness level	3,052.94	2,629.74	-423.20	-13.86
Very Low High Greenness level	1,654.76	1,501.98	-152.78	-9.23
No Vegetation	22.54	25.34	2.80	12.42
Total	26,879.97	26,674.72	-205.25	-0.76

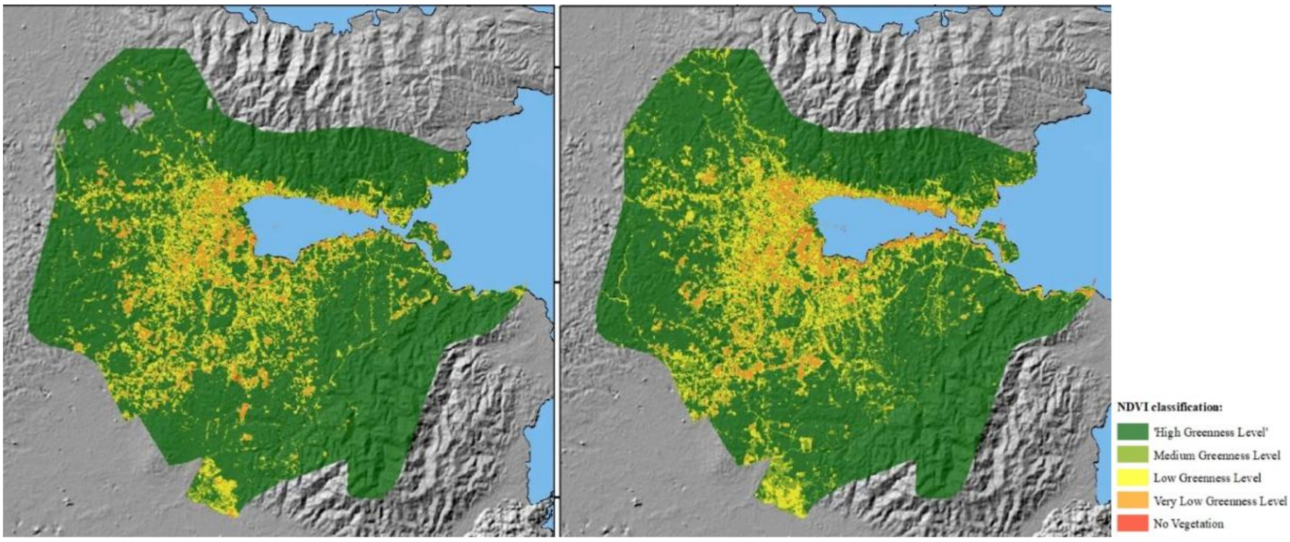

Figure 2. Normalized difference vegetation index (NDVI) of Kendari City in 2014 and 2024

The statistics in Table 1 demonstrate that the high greenness class grew by 8.21% (1,493.73 ha) as a result of the Southeast Sulawesi Provincial Forestry Service's river basin rehabilitation initiative, particularly in Kambu and Poasia Villages. However, this good trend contrasts with a steep drop in medium and low greenness levels, which fell by 28.44% and 13.86%, respectively. These decreases point to the change of moderately vegetated zones into built-up regions, especially in the urban core and transitional districts. The Very Low Greenness class also decreased significantly (-9.23%), indicating that marginal vegetated regions were being lost to development.

Meanwhile, non-vegetated regions (no vegetation) rose by 12.42%, primarily in central Kendari and previously classed as highly vegetated. This increase in impervious surfaces suggests that urban densification and land-use transformation are ongoing, consistent with findings from Manila, Philippines [4]; Kelantan, Malaysia [13]; Kunming, China [5]; and Mysuru, India [6], where rapid urbanization resulted in vegetation degradation and the expansion of built-up land.

Overall, Kendari City's total vegetated area declined from 26,879.94 ha in 2014 to 26,674.71 ha in 2024, a net loss of 205.23 ha (-0.76%). Although the percentage reduction is slight, it represents a significant biological transition from naturally vegetated land to impermeable urban surfaces. This transition has a direct impact on thermal comfort, groundwater penetration, and the stability of urban micro-ecosystems [14].

Low NDVI values are found primarily in the city center and recently constructed areas, indicating a decreased natural ability to regulate surface temperature and humidity. This state increases the vulnerability to the urban heat island (UHI) phenomenon. In contrast, suburban areas with persistently high NDVI values [15], particularly in the northern and southern districts, are significant natural buffers that should be maintained and integrated into climate adaptation plans and long-term sustainable urban design.

The general spatial pattern is consistent with data from other tropical cities [16-18], suggesting that highly built-up regions have lower NDVI values, indicating both a loss of plant cover and a weaker ecological buffering capability in the urban landscape.

3.2 Normalized difference moisture index (NDMI)

The NDMI research shows the regional variance and temporal dynamics of land moisture and vegetation water content in Kendari City from 2014 to 2024 (Table 2 and Figure 3). The findings show a significant shift in moisture distribution patterns over the previous decade, which is linked to vegetation change and urbanization.

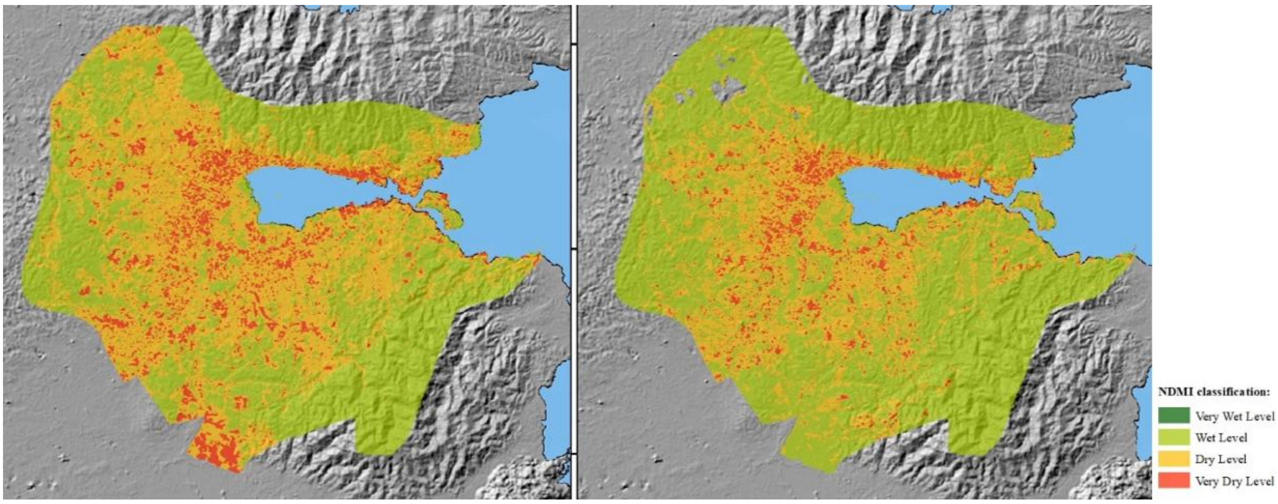

Figure 3. Normalized difference moisture index (NDMI) of Kendari City in 2014 and 2024

As shown in Table 2, between 2014 and 2024, wet surface areas grew by 36.28% (4,546.45 hectares), showing better soil and vegetation wetness in numerous parts of the city, particularly in northern and southern suburban zones with higher vegetation density. This increase in NDMI matches spatially to places with high NDVI values, indicating that thick vegetation plays an important role in maintaining surface moisture levels.

Table 2. NDMI class

NDMI Class	Area (ha)		Change	
	2014	2024	ha	%
Very dry level	2,606.26	1,412.50	-1,193.76	-45.80
Dry level	11,740.84	8,178.25	-3,562.59	-30.34
Wet level	12,531.21	17,077.66	4,546.45	36.28
Very wet level	0.00	0.06	0.06	
Total	26,878.31	26,668.47	-209.84	-0.78

In contrast, both the very dry and dry categories showed immense reductions of -45.80% and -30.34%, respectively, indicating a significant decline in arid zones that were widespread in 2014. These dry zones were primarily found in central and western Kendari, which have had major urbanization and infrastructure development. The change of permeable vegetated surfaces to impermeable built-up areas has most certainly impacted local hydrological processes, diminishing soil water retention capacity and increasing surface runoff.

The overall moisture distribution pattern indicates a spatial separation between the urban core and the vegetated periphery. The core districts (Kadia, Mandonga, and Wua-Wua) are significantly drier due to the prevalence of built-up areas, but the outer districts (Kambu, Poasia, and Abeli) have higher moisture levels due to increased vegetation cover. This is consistent with observations from other tropical urban environments, where plant loss and land conversion cause localized drying trends, whereas maintained green zones maintain higher moisture content and microclimatic balance [19, 20].

Although the total NDMI-based area declined by -0.78%, the increase in "Wet Level" regions suggests a partial recovery of vegetated land or the impact of improved rainfall patterns throughout the research period. However, the unequal geographical distribution of wet and dry zones demonstrates that urban expansion continues to exert significant localized pressure on surface moisture dynamics. Overall, the NDMI research highlights the strong relationship between vegetation health and density and surface moisture retention, emphasizing the necessity of protecting vegetated areas in urban development. Green infrastructure, such as urban woods, rain gardens, and permeable surfaces, may improve moisture retention and offset the detrimental consequences of urban dryness and heat building in Kendari City.

3.3 Land surface temperature (LST)

LST is a useful indicator for assessing the impact of urbanization, land-use change, and local climatic dynamics on thermal comfort [21]. The analysis reveals that Kendari City experienced significant surface warming between 2014 and 2024, which was linked to both physical land modification and spatially uneven vegetation changes.

In 2014, the city's surface temperature distribution was dominated by moderate to low temperature zones (22.0-23.5°C), especially in suburban areas with lush vegetation and undulating terrain (Figure 4). These colder zones, visually represented by green and yellow tones, corresponded to areas with dense vegetative cover and minimal development. Higher surface temperatures (red zones) were concentrated around the city center, particularly in Kadia, Mandonga, and Poasia, which were already densely populated and urbanized. This study confirms earlier results that the temperature in Kendari City rose by about 2.44°C from 2001 to 2014 [22].

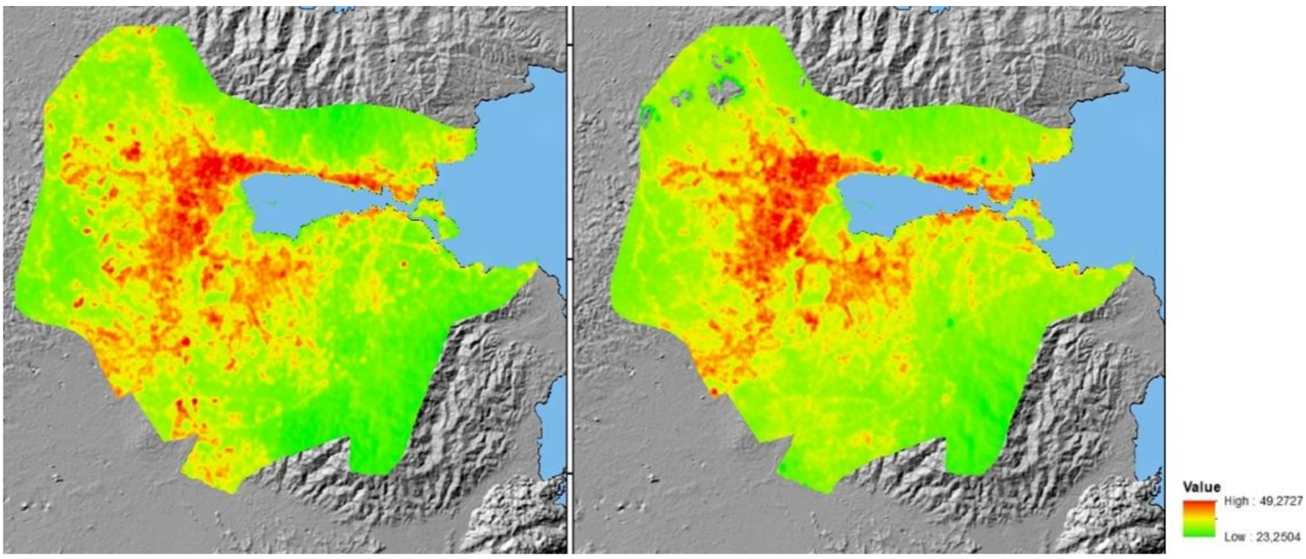

Figure 4. Land surface temperature (LST) map of Kendari City in 2014 and 2024

By 2024, high-temperature zones (> 24.5°C) had expanded dramatically, resulting in continuous heat clusters in the urban core. The quantitative classification (Table 3) shows a large decrease in low-temperature areas (-41.99%) and a corresponding increase in high- and very-high-temperature classes (+27.35% and +204.36%, respectively). The average LST increased from 22.6°C in 2014 to 25.1°C in 2024, representing a +2.47°C increase over the decade.

These results reveal that surface warming in Kendari is not evenly distributed but rather concentrated in the central and western regions. The urban heat island (UHI) effect has gotten worse, with rising temperatures in densely populated areas and a gradual extension into suburban zones like Kambu, Poasia, and Puuwatu, where high-temperature areas now account for more than 90% of total surface area. This evolution is mostly due to land conversion, infrastructural expansion, and the widespread use of impermeable materials, mainly asphalt and concrete, which absorb and store solar radiation more efficiently [23, 24].

Table 3. Distribution of LST classes

LST Class (°C)	Area (ha)		Change	
	2014	**2024**	**ha**	**%**
Low (< 21.5)	2,885.42	1,674.20	-1,211.22	-41.99
Moderate (21.5 - 23.5)	14,512.37	11,852.09	-2,660.28	-18.33
High (23.5 - 25.5)	8,932.18	11,374.61	2,442.43	27.35
Very high (> 25.5)	550	1,674.00	1,124.00	204.36
Total	26,879.97	26,674.72		

Global warming exacerbates this local effect; climatic projections forecast a global average temperature rise of 1.3-1.8°C [25], adding to the thermodynamic stress already present in tropical cities. These variables emphasize the significance of integrated climate-responsive urban design, which includes increasing green open spaces, planting urban trees, and adopting sustainable drainage systems to reduce heat accumulation and maintain hydrological balance. Integrating ESG-based spatial planning will allow local governments to manage urban demand more sustainably while achieving goals for adapting to climate change.

Despite the overall rise in surface temperature, the study discovered an 8.21% increase in "High Greenness" locations from 2014 to 2024. At first glance, the results appear contradictory: increased vegetation should theoretically reduce surface temperatures. However, a closer spatial study resolves this quandary.

The increase in NDVI values was predominantly centered in the Kambu and Poasia Districts, where government-led reforestation and watershed rehabilitation efforts took place between 2018 and 2023. These efforts were effective in restoring green cover and improving microclimate conditions in remote areas. However, these vegetated increases were spatially restricted and fragmented, unable to compensate for the significant loss of vegetation and increase in heat-emitting surfaces in the urban core districts (Kadia, Mandonga, and Wua-Wua).

In this area, land-use transformation advanced rapidly: built-up density increased, impermeable surfaces increased by approximately 12%, and evapotranspiration capacity declined drastically. As a result, the overall city thermal balance remained positive (warming), albeit some outlying areas saw local cooling effects. The results demonstrate geographical imbalance rather than contradiction: urban densification in the center surpassed ecological restoration in the periphery.

This finding is consistent with observations from other rapidly developing tropical cities, such as Manila [4], Kunming [5], and Mysuru [6], where local greening efforts coexist with citywide warming due to uneven land-use distribution, fragmented green spaces, and anthropogenic heat emissions. In each scenario, vegetation growth outside of the city center only provides local relief and has little impact on regional LST trends.

3.4 Correlation between NDVI and LST

The correlation between NDVI and LST suggests that vegetation plays an important role in controlling land surface temperature [26]. A correlation analysis between NDVI and LST yields a coefficient of -0.06610 (Table 4). This indicates that greater NDVI values result in lower LST values, and vice versa. High NDVI values suggest thick, healthy plant cover and lower surface temperatures. In contrast, locations with low NDVI, such as built-up areas (city centers), have greater temperatures due to a lack of flora capable of absorbing and decreasing heat via evaporation.

Table 4. Correlation between NDVI and LST in Kendari City

	NDVI	**LST**
NDVI	1	
LST	-0.6610	1

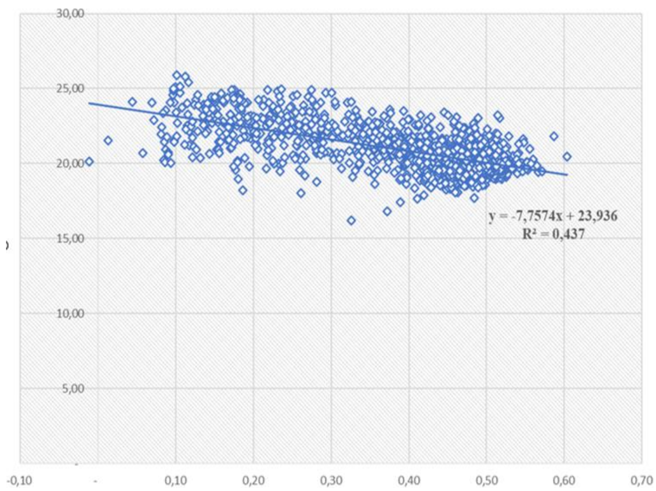

Figure 5. Correlation between NDVI and LST in Kendari City

The association graph between NDVI and LST exhibits a negative linear trend with the equation $y = -7.7574x + 23.936$ and a coefficient of determination $R^2 = 0.437$ (Figure 5). This suggests that vegetation cover variations account for 43.7% of LST variance, whereas 56.3% is explained by other factors such as surface material type, surface albedo, and human activities. Thus, while vegetation helps reduce land surface temperature, other things also contribute to increased surface temperature, which affects the urban heat island (UHI). As a result, to keep urban environmental temperatures stable, a comprehensive approach that combines vegetation planning and sustainable urban design is required.

3.5 Correlation between NDVI and NDMI

NDVI and NDMI are useful markers for monitoring vegetation and soil moisture levels [27]. NDVI measures the density of vegetation, whereas NDMI monitors the amount of water in the soil or vegetation. The correlation coefficient between NDVI and NDMI is 0.90817 (Table 5). This suggests that higher humidity will boost vegetation density, whereas water shortages may reduce it. The dependency of vegetation on water availability suggests a strong ecological response to local climate and hydrological conditions [28].

Table 5. Correlation between NDVI and LST in Kendari City

	NDVI	NDMI
NDVI	1	
NDMI	0.90817	1

The graph demonstrating the association between NDVI and NDMI produced a regression equation of y = 0.7838x - 0.1047, and R^2 = 0.8248 (Figure 6). This reveals that NDVI accounts for 82.48% of the variation in NDMI. This strong positive linear association suggests that when the NDVI increases, so does the NDMI. In other words, a greener and healthier plant (high NDVI values) has higher moisture content (high NDMI values). This indicates that, in an ecosystem context, the local vegetation is highly dependent on moisture to maintain its density and health. As a result, continuous monitoring of these two indicators is extremely beneficial in promoting conservation and climate adaptation measures in urban settings, such as water and soil conservation and the creation of sustainable green spaces.

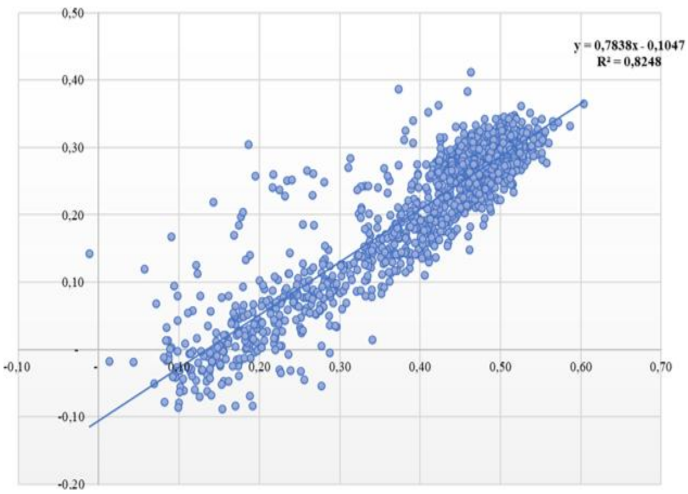

Figure 6. Correlation between NDVI and NDMI in Kendari City

3.6 Correlation between NDMI and LST

The correlation between NDMI and LST is negative, with a value of -0.76508 (Table 6). The linear regression equation y = -10.403x + 23.007 and R^2 = 0.5853 show that changes in NDMI represent 58.53% of the variation in LST (Figure 7). High NDMI tends to lower land surface temperature (LST) by natural cooling via evapotranspiration, but low NDMI tends to raise surface temperature, particularly in places with little vegetation [29]. This study suggests that the NDMI indicator could be used to monitor microclimate conditions, mitigate drought risks, and reduce the urban heat island impact.

Table 6. Correlation between LST and NDMI in Kendari City

	LST	NDMI
LST	1	
NDMI	-0.76508	1

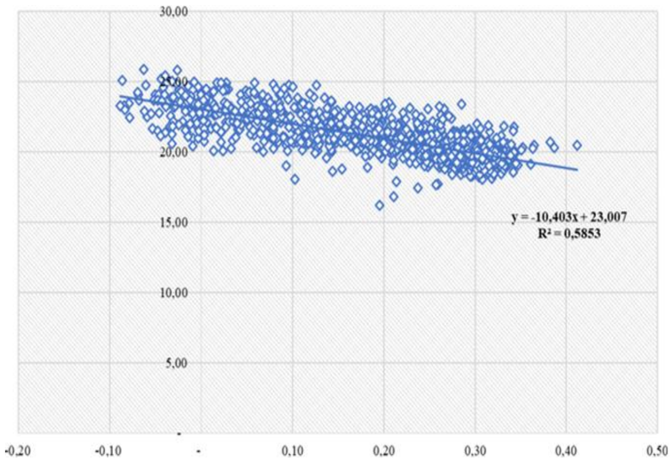

Figure 7. Correlation of LST and NDMI in Kendari City

3.7 The impact of NDVI and LST on NDMI

The regression analysis revealed a significant correlation between NDVI and LST on NDMI. The multiple correlation coefficient (R) of 0.9343 and R^2 = 0.8729 showed that changes in NDVI and LST could explain 87.29% of the differences in NDMI (Table 7). This indicates that the created model has high predictive skills.

NDVI exerts a substantial positive influence on NDMI (correlation coefficient = 0.6169), signifying that regions with thick and robust vegetation possess elevated moisture levels. This illustrates the consistency of vegetation's ecological role in preserving soil moisture via shadow protection and evapotranspiration processes. Conversely, LST exhibits a substantial negative correlation with NDMI (correlation coefficient = -0.02), suggesting that rising surface temperatures lead to diminished soil moisture as a result of heightened evaporation and decreased vegetation cover.

The regression model shows that NDMI = 0.4104 + 0.6169 (NDVI) - 0.02 (LST), meaning that if NDVI goes up by one unit, NDMI increases by 0.6169 units, but if LST goes up by one degree, NDMI decreases by 0.02 units. This signifies that the reduction of plant cover and diminished soil moisture directly influence the rise in surface temperatures. In contrast, regions with elevated NDVI and NDMI values continue to have lower and stable surface temperatures. This finding affirms that plants and soil moisture significantly mitigate local warming effects and sustain urban ecological balance. Consequently, urban spatial planning focused on conserving vegetation cover, enhancing green infrastructure, and regulating impermeable surfaces is crucial for mitigating moisture loss and sustainably managing the city's microclimate, particularly in the context of urbanization and global climate change.

Table 7. The impact of NDVI, LST, and NDMI of Kendari City

Regression Statistics								
Multiple R				0.93433254				
R^2				0.872977295				
Adjusted R Square				0.872796993				
Standard Error				0.03756636				
Observations				1412				
	Df		*SS*		*MS*	*F*	*Significance F*	
Regression	2		13.66566643		6.832833216	4841.752524	0	
Residual	1409		1.98842505		0.001411231			
Total	1411		15.65409148					
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95%*	*Upper 95%*
Intercept	0.4104	0.0225	18.21	1.10315E-66	0.3662	0.45	0.37	0.45
NDVI	0.6169	0.0109	56.48	0	0.5954	0.64	0.59	0.64
LST	-0.02	0.0009	-23.12	1.5038E-100	-0.02	- 0.02	-0.02	-0.02

4. CONCLUSIONS

Vegetation has a considerable impact on surface temperature and moisture balance in Kendari City. The 205.25 hectares of vegetation loss and +2.44°C increase in LST over a decade show the repercussions of unrestrained urbanization. Strong connections between NDVI, LST, and NDMI show that plant removal not only elevates surface temperatures but also speeds up soil moisture depletion. Urban policies should therefore incorporate climate-sensitive land use planning by establishing urban green corridors and public parks in high-temperature zones such as Kadia, Mandonga, and Wua-Wua; conserving vegetation in Kambu and Poasia as ecological buffers; and promoting green infrastructure and sustainable drainage systems to reduce impermeable surfaces. These initiatives have the potential to improve urban resilience, ecological stability, and thermal comfort, thereby enabling Kendari's long-term growth in the face of climate change. Reduce the detrimental consequences of urban dryness and heat buildup in Kendari City.

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