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Urban Heat Island Effect and Sustainable Planning: Analysis of Land Surface Temperature and Vegetation in Malang City

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ABSTRACT

This study investigates the spatial relationship between Land Surface Temperature (LST), Normalized Difference Built-Up Index (NDBI), and Normalized Difference Vegetation Index (NDVI) in Malang City, Indonesia. Utilizing satellite-based remote sensing data from Landsat 8 OLI/TIRS and Sentinel-2, the research analyzes the impacts of rapid urban expansion on temperature variation across the city. The results show a significant positive correlation between NDBI and LST, where a 0.1 increase in NDBI results in a rise of 1.075℃ in LST. Conversely, a 0.1 increase in NDVI leads to a decrease of 0.339℃ in LST, demonstrating the cooling effect of vegetation. The regression model explains 86.4% of the variation in LST (R^2 = 0.864), highlighting the role of land cover in regulating local temperatures. In 2024, the average LST in Malang City was recorded at 28.32℃, with the highest temperatures exceeding 34.64℃ in densely populated urban areas, particularly in the Klojen District. The study emphasizes the critical need for sustainable urban planning policies, such as increasing urban green spaces and adopting vegetation-based solutions in high-density zones to mitigate the Urban Heat Island (UHI) effect. These findings provide valuable insights for policymakers aiming to balance urban development with environmental sustainability.

1. INTRODUCTION

Urban areas are complex and dynamic ecosystem areas [1]. Cities that act as centers of community activities have a higher regional growth rate compared to the surrounding area [2]. Due to intense human activity and interaction, urban areas undergo significant changes in land cover and use as a result of population increase and economic development [3]. Due to population expansion and greater economic development globally, there has been a considerable increase in the movement of people to urban areas. Literature reviews demonstrate that over the past century, urbanization has grown at previously unheard-of rates in many parts of the world, and these growth rates don't appear to be slowing down [4]. The proportion of people living in cities worldwide rose from 30% in 1950 to 55% in 2018 and is expected to reach 68% by 2050 [5]. Population density, building density, the size of built-up regions particularly residential areas, which are typically larger and the number of facilities facilitating urban activities are physical characteristics that define a city's development [6].

A major environmental indicator, ground cover has detrimental effects on biodiversity, increased water runoff, loss of agricultural land, and microclimate change. The growing number of artificial surfaces that are impermeable increases the risks associated with surface water runoff and modifies the microclimate within cities [7]. Localized temperature differences can have negative impacts on humans and the environment by inhibiting the supply of clean air, increasing energy consumption, losing biological controls, and affecting public health [8]. Such changes in microclimate conditions can make the environment more sensitive and increase human health risks [9]. For example, a US study found that there were 1,373 additional deaths per year (2008-2017) due to extremely hot days in summer [10].

Malang City is part of the Greater Malang Metropolitan Area, which also includes Malang Regency and Batu City. After Surabaya City, Malang City is the second-largest city in East Java, which has shown rapid development dynamics [11]. Every year, the average population of Malang City has increased where in 2020-2023 the population growth rate was 0.13% [12]. One of the physical forms of changes in land cover conditions in Malang City is shown by the area of green space for rice fields which has decreased in 2011-2023 to 305 hectares [12]. Furthermore, there has been a great deal of urban density in the city center and its environs in terms of building density, automobile density, and population density [13]. The density is caused by a significant increase in the area of built-up land where in 2012-2020, there was an increase of 6% to 56.05 km2 or 51% of the total area of Malang City [14]. Except for the Southeast and South regions, all areas of Malang City have nearly equal building densities; however, given the city's annual population growth, the less densely populated areas may eventually become productive urban area [11]. Continuous uncontrolled development has the potential to affect the structure and spatial pattern of Malang City which can have an impact on environmental sustainability.

Research has shown that modifications to land use and land cover play a major role in the phenomenon of global climate change [15]. Urbanization and industrialization have the potential to alter the atmosphere and land surface, which could modify the thermal characteristics of urban regions and make them warmer than the nearby non-urban areas [16]. Because most metropolitan areas are made up of impermeable surfaces that radiate heat into the surrounding environment and absorb radiation, the expansion of urban areas causes an increase in LST [17]. In other words, urbanization and increased built-up areas can increase LST due to the increased use of artificial materials with high heat capacity and conductivity [18]. Since the mid-20th century, human activities have been closely linked to global warming based on observations of an increase in average global temperature [19]. In the last 21 years (1997-2018), the change in surface temperature of Malang City increased by more than 2°C due to land use change [20]. If the rate of urbanization and the expansion of built-up areas continue without appropriate urban planning measures, the impervious surface area will be greater, which in turn has implications for increasing LST which is getting worse.

There are numerous ways to measure LST, but the only practical method for analyzing the temporal and spatial fluctuations of LST across broad regional ranges is satellite-based remote sensing technology [21]. Remote sensing is an alternative to measure thermal conditions in urban environments with satellite data sources that have been widely applied in urban environmental studies [7]. The NDVI and NDBI distributions are highly correlated with the LST distribution [22]. Commonly used indicators to examine the relationship between LST and vegetation and built-up area are NDVI and NDBI [23].

There is a close relationship between the distribution of urban LST and the indices of vegetation and built-up area, so researchers want to analyze the relationship between LST and the two indices to determine the magnitude of the influence of each index on LST distribution. The findings of the interaction between LST, NDBI, and NDVI are expected to have objectives of this research consist of three, (1) Understanding Malang City's LST distribution situation will affect how policies are made for next urban planning and design initiatives in the city. Therefore, the 2024. (2) To determine the condition of NDBI and NDVI distribution as an index of built-up area and vegetation in Malang City in 2024. (3) To determine the correlation between the three variables using statistical methods such as linear regression.

2. METHODOLOGY

2.1 Study area

In the province of East Java, Malang City is the second-biggest city after Surabaya with an area of 111.077 km^2 which is at an altitude of 445-526 mdpl [12]. The lowest elevation (445 masl) is in Kedungkandang and Sukun districts while the highest point (526 masl) is in Lowokwaru district [24]. The landscape of most areas in Malang City is 91% or 52 district are lowlands with a slope of 0-15% and there are only 5 districts with topography in the form of slopes or peaks. The coordinates of Malang City are 7.06° - 8.02° South Latitude and 112.06° - 112.07° East Longitude.

The population of Malang City is one of the factors that led to its selection as the research region, the city's population growth rate is normally higher each year. Malang City's population in the first semester of 2024 was 880,787 compared to 851,298 in 2015. Based on BPS Malang City, in 2023 the minimum temperature of Malang City occurs in September, namely 14.80 degrees Celsius. While the maximum temperature occurs in October, namely 34.00 degrees Celsius. The highest average temperature is recorded in October at 27.30 degrees Celsius, while the lowest average temperature is recorded in July at 24 degrees Celsius. Then for the lowest average air humidity occurred in October with an average humidity of 60.80% and the highest average air humidity occurred in February with an average humidity of 80.40% [12].

Below is a picture of the study location. Figure 1 shows the location map of Malang City with East Java Province. Figure 2 shows an image map of the administrative boundary of Malang City which consists of 5 districts that are the location of the study.

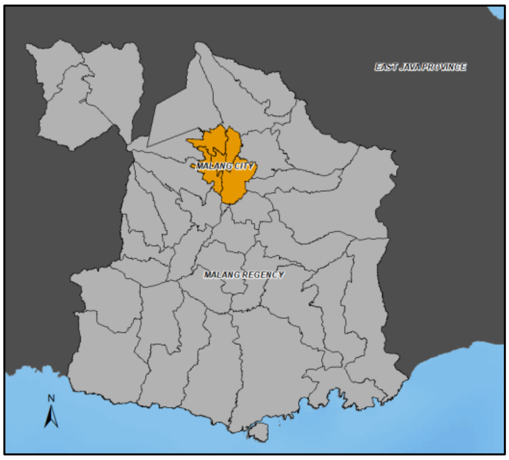

Figure 1. Orientation map of Malang City

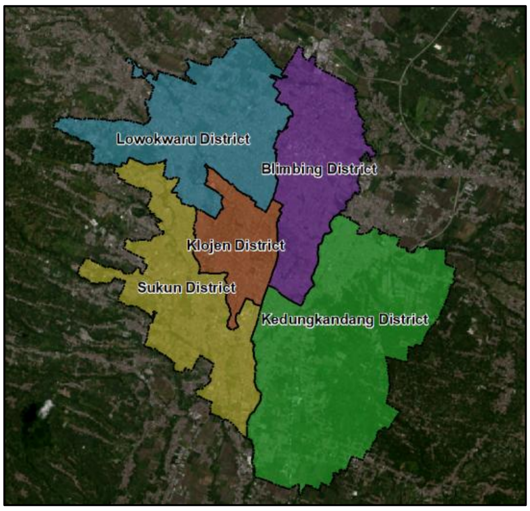

Figure 2. Administrative map of Malang City

2.2 Data collection

The data used in this research is entirely sourced from the use of satellite imagery via remote sensing methods. The satellite imagery used is Landsat 8 OLI/TIRS for LST distribution data and Sentinel-2 satellite imagery for NDBI and NDVI data. Researchers have used these two satellite images extensively, particularly in urban spatial environmental studies. They have a moderate to medium spatial resolution.

2.2.1 Landsat 8 OLI/TIRS

Landsat 8 was launched on February 11, 2013. Landsat 8 imagery can be freely accessed via the U.S. Geological Survey (USGS) website at https://earthexplorer.usgs.gov in the geotagged image file format (GeoTIFF). The USGS data center provides Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager/Thermal Independent Sensor (OLI/TIRS) sensors on the Landsat data used for this research. The OLI sensor in Landsat 8 imagery has 9 bands, while the TIRS sensor has 2 bands, namely band 10 and band 11 with different characteristics [22]. The spatial resolution on the OLI sensor is 15 m to 30 m, while the resolution on the TIRS sensor is 100. In this research, Landsat imagery is used to process LST distribution data for Malang City in 2024.

2.2.2 Sentinel-2

Sentinel-2 is made up of two constellation spacecraft, Sentinel-2A and Sentinel-2B that orbit the poles at a height of 786 km in a sun-synchronous orbit. Both are operated by a control team from ESA'S European Space Operations Center (ESOC) Darmstadt, Germany. Sentinel-2 satellite imagery can be obtained freely via the website https://scihub.copernicus.eu. The Sentinel-2 satellite image consists of 13 spectral bands with a spatial resolution of 10 m, 20 m, and 60 m. This product has been projected ortho UTM/WGS84 and uses a Digital Elevation Model (DEM) projected on cartographic coordinates. Basically, the Sentinel-2 satellite image is a medium resolution image but is high enough to be used for land surface analysis. In this research, Sentinel-2 imagery is used to process NDBI and NDVI distribution data for Malang City in 2024.

2.3 Remote sensing theory

Remote sensing is composed of two words, namely remote which means obtaining information without direct contact and sensing which means obtaining information on the condition of the earth's surface (Canada Center for Remote Sensing, 2010) [25]. The tools used are usually satellites, drones or unmanned aircraft, airplanes, hot air balloons, and so on. In order to comprehend the spatial and temporal variations of fundamental physical attributes depending on various land use patterns, field surveys using remote sensing devices are essential [26]. Environmental monitoring, management, and planning depend on processing current, reliable data on land cover and environmental conditions [16]. Utilizing Landsat 8 and Sentinel-2 satellite image data, remote sensing techniques were applied in this study.

2.4 Pre-processing for satellite imagery

Remote sensing data from recorded satellite imagery is generally raw data. So, before processing satellite images, image pre-processing is carried out. These processes include geometric correction, radiometric correction, and atmospheric correction. All three aim to improve the quality of the satellite images used. The three pre-processing stages are applied to the processing of Landsat 8 satellite imagery. As for the Sentinel 2 level 2A image, the geometric and radiometric correction stages are not carried out because the level 2A product has been geometrically and radiometrically corrected and has a Bottom of Atmosphere reflectance so that the next correction process is atmospheric correction to change the image pixel value from TOA reflectance to at surface reflectance [27].

2.4.1 Geometric correction

Geometrics are geographical positions that relate to spatial distribution. Geometric information contains georeferenced data, both the position and the information in it. Geometric correction of imagery is the transformation of imagery so that the image has the properties of a map in shape, scale, and projection [28].

2.4.2 Radiometric correction

Radiometric correction is the initial stage of data processing before analysis of the image data. This correction process includes correction of sensor-related effects that increase the contrast of each pixel. This correction aims to make the recorded objects easier to analyze to produce data/information according to the existing conditions. Radiometric correction in the form of shifting the gray value of pixel elements in the image to make it closer to the proper value and to improve the visual quality of the image [28].

2.4.3 Atmosphere correction

In atmosphere correction related to atmospheric correction, there are two kinds of corrections, namely ToA (Top of Atmosphere) and BoA (Bottom of Atmosphere). ToA correction is a correction to the image to eliminate radiometric distortion caused by the position of the sun. Meanwhile, BoA correction is a correction to the image by converting the digital number value into BoA radians. The atmosphere can affect the passage of electromagnetic waves, causing errors in the image data that can potentially provide inaccurate information. These errors can be minimized with atmospheric correction [29].

2.5 Land surface temperature (LST)

The contact between the Earth's surface and atmosphere produces heat that is capable of affecting human beings, which is known as land surface temperature (LST). Aspects of the weather like wind speed, solar radiation, and surface characteristics all have an impact. Reduced wind speeds, for instance, can result in higher LST levels [30]. In other words, LST has diverse values mainly due to variations in reflectance and ground surface roughness [31]. The distribution of LST in this study is used in describing areas with urban heat spots (UHS) in Malang City and its relation to the land use index classification.

However, band 10 in the Landsat 8 TIRS image has a better ability to identify areas with high temperatures compared to band 11 because of the greater calibration uncertainty in band 11 [32]. Band 10 is more effectively used to identify thermal anomalies caused by geothermal manifestations. So this study uses band 10 to process LST distribution data. The three factors required to process land surface temperature (LST) are mean atmospheric temperature, atmospheric transmittance, and ground emissivity, all of which are included in the TIRS data from Landsat 8. The spatial resolution of the LST data sourced from Landsat 8 satellite imagery is 30 m x 30 m. The LST pixels were then extracted with the administrative boundaries of Malang City for further analysis. ArcGIS 10.4.1, ENVI 5.3, and QGIS 3 software were used for image data processing and mapping in this study.

2.6 Normalized Difference Built-Up Index (NDBI)

Normalized Difference Built-Up Index (NDBI) is an index to estimate the level of built-up area in an image. NDBI is a spectral index that is commonly used in analyzing the relationship between built-up area and LST in urban areas because it has a significant correlation with LST values [22]. NDBI classification data in this study was obtained through data processing results sourced from Sentinel-2 satellite imagery.

NDBI values range from -1 to 1 [26]. Higher NDBI values indicate denser buildings. The bands used to determine NDBI values during the extraction process using Sentinel-2 photos are the Short Wavelength Infrared (SWIR) band and the Near Infrared (NIR) band. The NDBI value is calculated using the following equation.

$$NDBI = (SWIR - NIR) / (SWIR + NIR)$$

NDBI index values are classified into 4 classes. The classification is based on the level of building density consisting of non-building areas to the highest building density. Table 1 below is the NDBI classification [33].

Table 1. NDBI classification

Class	NDBI Value	Building Density Level
1	-1 < NDBI < 0	Non Settlement
2	0 < NDBI < 0.1	Sparse Settlement
3	0.1 < NDBI < 0.2	Dense Settlement
4	0.2 < NDBI < 0.3	Very Dense Settlement

2.7 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is the most commonly used index for extracting vegetation elements in an image. According to Tucker in the study of Guha et al. [34], the NDVI vegetation index is often analyzed together with the LST value because the vegetation index has an effect in reducing the LST value and shows a negative correlation with the LST value.

NDVI data processing in this study uses data sourced from Sentinel 2-A satellite imagery for 2024. The near infrared (NIR) band 8 and band 4 red are used to create NDVI values, which are then used to identify the type of land use. Positive values correspond to vegetation, whereas negative values correspond to built-up areas, open land, and water [35]. The processing of NDVI values with Landsat 8 imagery utilizes band 4 Red and band 5 Near Infrared (NIR).

The vegetation index has values that range between -1 and +1. Dense and strong vegetation can be seen with higher positive NDVI levels [9]. Meanwhile, lower values indicate non-vegetated land. NDVI values are calculated using the following equation.

$$NDVI = (NIR - RED) / (NIR + RED)$$

In this study, the classification of NDVI index values refers to the classification of land greenness with a total of 5 classes. The classification is based on the level of vegetation density, from non-vegetated land to land with high vegetation density. The following is the NDVI classification [36] (Table 2).

Table 2. NDVI classification

Class	NDVI Value	Greenness Level
1	-1 < NDVI < -0.03	Non Vegetation
2	-0.03 < NDVI < 0.15	Very Low Vegetation
3	0.15 < NDVI < 0.25	Low Vegetation
4	0.25 < NDVI < 0.35	Medium Vegetation
5	0.35 < NDVI < 1	High Vegetation

2.8 Correlation between LST, NDBI, and NDVI

Regression analysis is a statistical procedure that makes use of multiple variable modeling and analysis methods to evaluate the relationship between two or more variables. This process aims to determine the relationship between one dependent variable and one or more independent variables. With specific types of data, multiple regression is used when there are two or more independent variables in the equation; if there is just one independent variable, it is called a simple regression model [37].

Linear regression methods have been commonly used in many studies that examine the relationship between LST and urban landscapes. However, because of seasonal variations in land cover data, intricate landscape architecture, and variety in urban morphology, regression methods' correlation results may not be linear. In this case, linear regression models can be useful for analyzing trends and providing an overview of the relationship between LST and land cover [8].

Multiple linear regression is the method used in this study's regression analysis to ascertain the extent to which the built-up area and vegetation index variables, the NDBI and NDVI have an impact on LST values. In the multiple linear regression test, land surface temperature as the dependent variable (Y) and independent variable (X) consists of two, namely vegetation density (X_1) and building density (X_2). In analyzing the influence of the two variables, the linear regression method is used with SPSS software. The analysis's findings are anticipated to serve as a guide for determining the extent to which land conversion into built-up regions affects thermal features while creating sustainable spatial goods. Multiple linear regression is based on the following probabilistic model.

$$Y=a_0+a_1.X_1+a_2.X_2+\ldots+a_n.X_n$$

where, Y=Dependent variable value prediction; a_1=First independent variable; a_2=Second independent variable; a_n=n independent variable; a_0=Constant; X_1=First independent variable coefficient; X_2=Second independent variable coefficient; X_n=n independent variable coefficient.

The research unit used to calculate linear regression in this research is a grid. The grid size used is 300 meters × 300 meters. The number of grids formed is 1117 grids which will then become samples for calculating linear regression to look for correlations between LST, NDBI and NDVI. The use of a 300 m × 300 m grid was chosen by researchers because the grid size is considered to have sufficient level of detail to produce the average value of the data to be calculated to get fairly accurate results. In addition, with this grid size, a sample of 1117 samples were produced which has far exceeded the minimum sample requirement needed, which is 74 samples based on the formula from Roscoe in the book "Research Methods for Business" with the sample requirement formula, namely the number of samples equal to 8 times the number of variables, namely 3 variables summed up to 50. So, it is expected that the analysis results have sufficient level of detail. The following is Figure 3 which shows the grid of this research area.

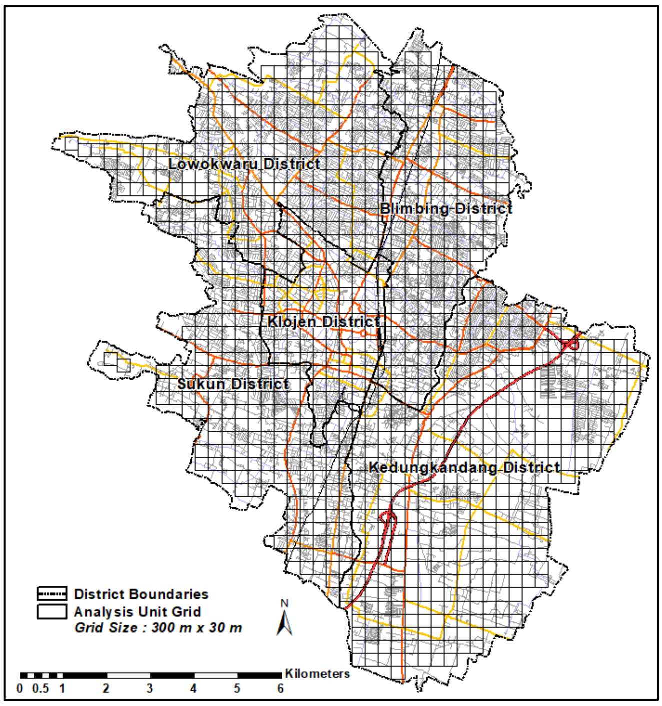

Figure 3. Grid map of research analysis unit

3. RESULT AND DISCUSSION

3.1 LST of Malang City 2024

The data of LST distribution in Malang City using remote sensing with Landsat 8 OLI/TIRS image thermal band 10 with an acquisition date of August 19, 2024. The trend of LST value processing results shows variations in LST distribution of Malang City 2024. Because each form of land use and cover has distinct thermal, moisture, and optical spectrum qualities, LULC generally has an impact on the local thermal environment [38]. One of the main factors influencing the chemical, physical, and biological activity occurring in the environment is LST [39]. The following figure shows the LST distribution of Malang City in 2024.

Figures 4 and 5 show how LST values are distributed in Malang City in 2024. It can be seen that the lowest LST point is 15.61℃ and the highest LST point is 34.64℃. The average LST of Malang City in 2024 is 28.32℃. Then the researchers also classified the LST value into 4 classes to get the distribution of variations suitable for analysis, namely low temperature to high temperature classes. The following is the area and percentage of each temperature class in Malang City.

Based on Table 3, the dominating LST in Malang City in 2024 is the high temperature class with an area percentage of 38.83% and followed by the low temperature class with a percentage of 27.18%. Meanwhile, the LST with the smallest area is the very low temperature class with a percentage of 10.61%. Through the classification results of LST distribution in Malang City, it can be seen that there are hot spots or hot spots scattered in the city area but tend to be centered in the central part of Malang City, namely Klojen District and parts of the four other districts bordering Klojen District. Meanwhile, the very low temperature class marked in green in the figure has a large area in Kedungkandang District, especially the eastern part. The difference in the condition of the LST distribution area of each district shows that there are differences in the characteristics of each district that can affect the LST value such as the type of land use and population distribution. The city's less densely and more sporadically vegetated areas experience high temperatures.

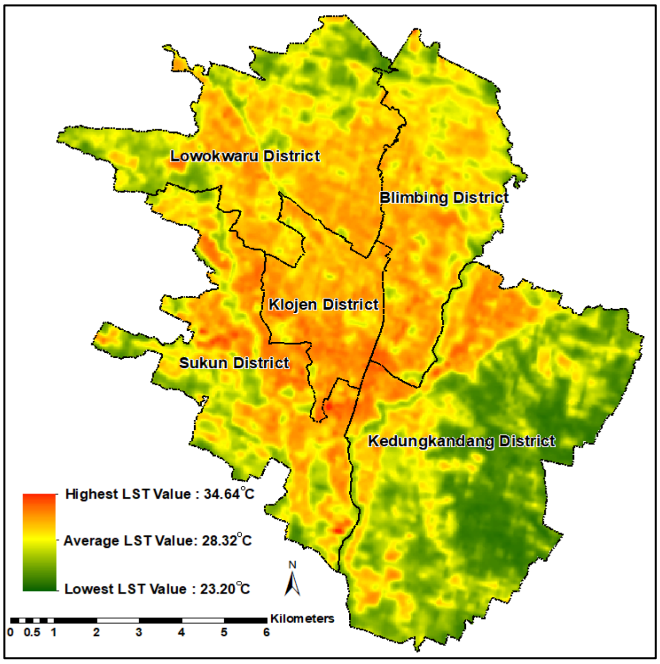

Figure 4. LST of Malang City 2024

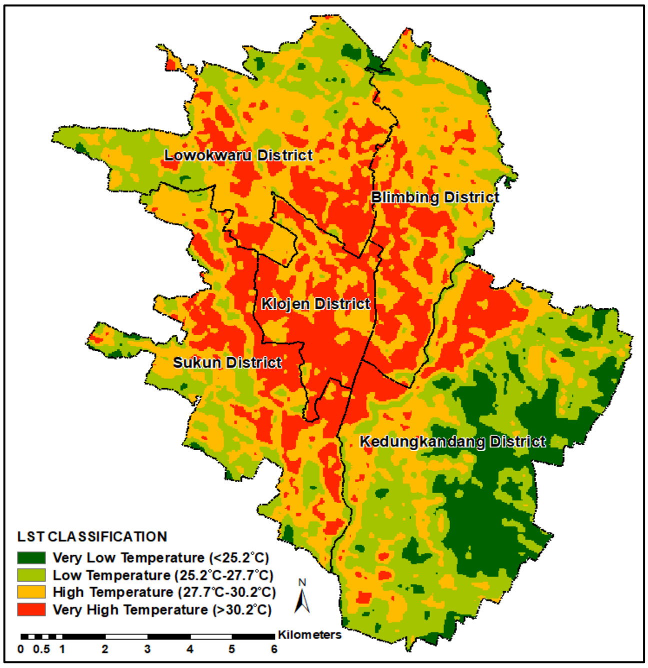

Figure 5. LST classification of Malang City 2024

Table 3. LST classification area of Malang City 2024

LST Class	LST Information	Area (km^2)	Percentage (%)
1	Very Low (<25.2°C)	11.76	10.61
2	Low (25.2°C -27.7°C)	30.11	27.18
3	High (27.7°C -30.2°C)	43.02	38.83
4	Very High (>30.2°C)	25.91	23.38

The existence of areas in Malang City with high to very high temperature classes shows that the problem of increasing temperature in Malang City is an issue that must be considered in the future. The main reason for the problem of increasing urban temperatures includes the provision of vegetation land that is insufficient for the needs of the city. It causes elements that can increase air temperature such as CO_2 and solar intensity cannot be dampened by vegetation due to the lack of availability of vegetation land or urban green open space (RTH) which should have the main function in regulating microclimate. This shows that there is a complex relationship between the condition of LST distribution and the type of urban land use so that an appropriate planning concept is needed to realize a sustainable urban environment.

Table 4. Area and average LST for each district of Malang City 2024

District	Area (km^2) LST Class 1	2	3	4	LST Mean (°C)
Blimbing	0.25	2.40	10.20	4.84	29.21
Lowokwaru	0.46	6.55	11.24	5.49	28.72
Klojen	0.00	0.06	3.25	5.52	30.44
Kedung kandang	10.74 .00	16.15 .00	9.08	3.80	26.86
Sukun	0.31	4.95	9.26	6.26	29.04
Total	**11.76**	**30.11**	**43.02**	**25.91**	

Based on Table 4, it can be seen how the LST distribution conditions of each district in Malang City. The district with the highest average LST is Klojen district at 30.44°C and the district with the lowest average is Kedungkandang district at 26.86°C. Through the distribution data of each district, it can be seen that there is a significant difference in the condition of the LST value between districts, which indicates that there are differences in characteristics between districts that are quite prominent.

Lower LST is often dispersed throughout Malang City's northern, southern, and eastern regions, which are primarily covered in plantations and other types of vegetated land cover. Meanwhile, higher LST tends to be scattered in the central area of the city, especially in Klojen District and some of the surrounding areas of the other four districts. Built-up areas, including communities, industry, and other regions, make up the majority of the land cover types in these locations. This indicates that the hottest parts of Malang City are its built-up areas, which are found in the center and surrounding areas, whereas the city's periphery especially its heavily vegetated north, east, and south has a lower distribution of LST.

This is consistent with other research that demonstrates how changes in land cover and use from vegetated to built-up areas due to urban growth will result in more variations in the thermal characteristics of urban areas [38]. According to Ma et al. in the study of Chen and Zhang [38], due to the varied nature of the ground surface, there may be changes in LST in urban contexts. Pixels with the same vegetation distribution or the same impervious surface distribution may have different LST values because the emissivity of each pixel may be different due to various factors such as soil moisture, vegetation characteristics.

The difference in LST conditions between regions is also affected by albedo. Albedo is the constant of sunlight reflection by a surface. The higher the albedo, the more light is reflected. In short, because different surfaces reflect different wavelengths of solar light differently, albedo provides essential information on soil structure. This is due to changes in the physical and chemical features of the soil surface. So that locations where the soil is fertile and has sufficient moisture and vegetation cover result in low albedo, but built-up areas are characterized by high albedo and subsequently elevated LST [26].

3.2 NDBI of Malang City 2024

Built-up area is the most important land surface feature in urban environments and has a direct influence on the distribution of LST. The spatial expansion of built-up areas is a very common phenomenon in urban areas, so the significance of NDBI is gradually increasing in the distribution of LST in urban environments [31]. Mapping built-up regions using the NDBI approach is a useful tool for tracking the rapid urban development that occurs there [38]. The data source of NDBI distribution in this study is Sentinel-2 imagery with an acquisition date of July 23, 2024. NDBI values are classified into 4 classes based on the level of building density from non-building classification to very high building density. The following figure shows the distribution of building density and its classification in Malang City in 2024.

Based on Figures 6 and 7, it can be seen how the 2024 NDBI value illustrates the distribution of building density levels in Malang City in 2024. The highest NDBI value is 0.705557, the lowest is -0.557164, and the average NDBI is -0.108953. Based on the NDBI value that is formed, it is then classified into 5 classes from non-building class to high building density level. The average figure actually does not illustrate the severe level of building density in Malang City due to the large amount of non-residential land in Malang City around 48.18% but it can be seen from visual observation that the distribution of buildings of the city, especially Klojen District, Blimbing District, and parts of the other three districts. In contrast, the Kedungkandang district has low NDBI values, which suggests that there are less built-up areas in the form of towns and that non-residential property, such as rice fields and plantations, predominates.

Based on Table 5, it is known that the dominating NDBI class in Malang City is non-settlement with a percentage of 48.18%. It can be seen on the map that the color that represents the non-settlement class, namely light beige, is more dominant than other classes, especially in the Kedungkandang District. This indicates that open space, rice fields, and gardens continue to make up the majority of Malang City's land area, which is used for non-building purposes. Meanwhile, the NDBI class with the smallest area is very dense settlement with a percentage of 13.57% which is generally located in the central part or center of Malang City especially especially Klojen district and the surrounding areas.

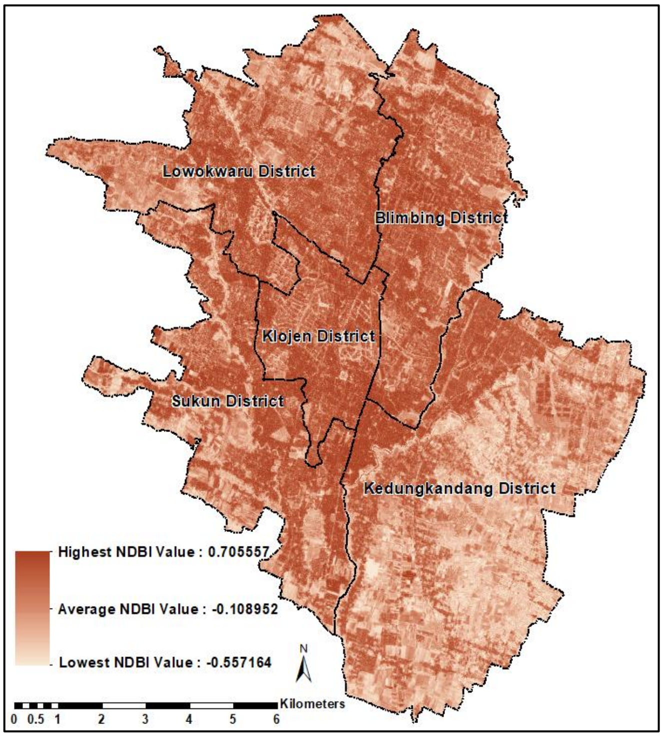

Figure 6. NDBI value of Malang City 2024

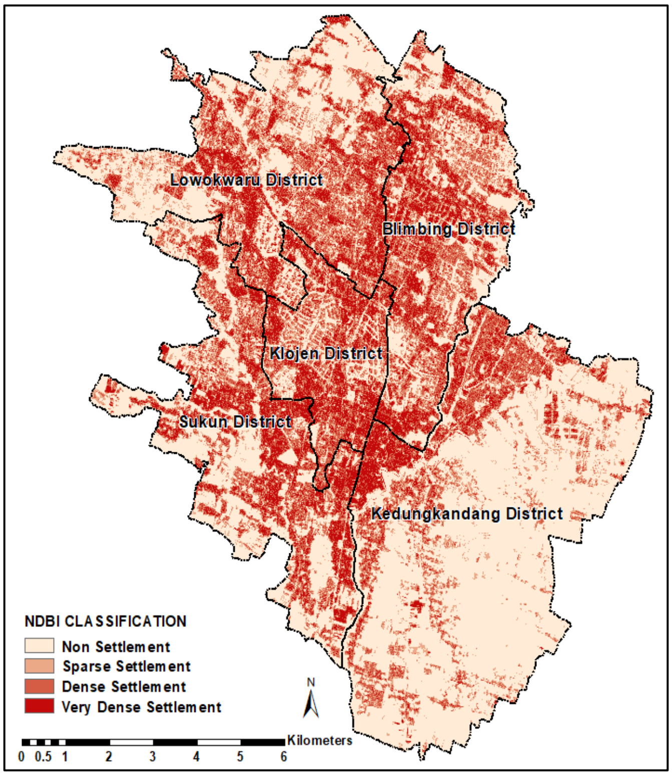

Figure 7. NDBI classification of Malang City 2024

Table 5. NDBI classification area of Malang City 2024

NDBI Class	NDBI Information	Area (km^2)	Percentage (%)
1	Non Settlement	53.47	48.18
2	Sparse Settlement	18.57	16.74
3	Dense Settlement	23.87	21.51
4	Very Dense Settlement	15.06	13.57

Table 6. Area and average NDBI for each district of Malang City 2024

District	Area (km^2) NDBI Class 1	2	3	4	NDBI Value Mean
Blimbing	5.59	3,66	5.19	3.27	0.059973
Lowokwaru	9.72	4.71	5.82	3.53	0.029928
Klojen	1.89	1.83	2.82	2.29	0.101665
Kedung kandang	27.60	4.90	5.06	2.27	-0.089732
Sukun	8.66	3.48	4.99	3.71	0.026167
Total	**53.47**	**18.57**	**23.87**	**15.06**	

Table 6 shows the building density of each district based on the NDBI index. The district with the highest average NDBI is Klojen at 0.101665 and the district with the lowest average is Kedungkandang which even has a negative value of -0.089732. The difference in average numbers shows a significant difference in building density conditions and even the NDBI value of Klojen also has a considerable difference from the other three districts. This shows that the intensity of buildings in Klojen District has a very high density and needs to be a special concern for the government and the community.

Although there is still plenty of non-residential land in the other districts, given the rapid urbanization of the population and the increasing growth rate, the need for land in the future will also increase. This will certainly affect future building density conditions if not managed properly. The existence of severe building density in certain areas can lead to various further urban problems such as slums, heavy vehicle activity, and so on.

3.3 NDVI of Malang City 2024

NDVI is one of several vegetation indices in remote sensing science which is widely used by researchers to analyze the proportion of vegetation cover on the earth's surface [40]. NDVI values are classified into 5 classes from non-vegetation to high vegetation. In this research, the data source used comes from Sentinel-2 satellite imagery. The following is an image showing the distribution of NDVI in Malang City in 2024.

Figures 8 and 9 illustrate the distribution of NDVI values in Malang City in 2024. The lowest NDVI value is -0.047520, the highest NDVI value is 0.902914, and the average NDVI is 0.528207. The average figure actually still shows the availability of a fairly good vegetation component in Malang City because it shows a high average NDVI value. However, it is evident that the green element in Figure 4 is not evenly distributed, with the green color concentrated only in the Kedungkandang District in the eastern and southern parts of Malang City, while other areas are dominated by the red color, indicating a low level of greenness or vegetation elements. Land cover in the form of plantations and rice fields appears to be the predominant green feature in Kedungkandang District. while the green elements in the central part of the city are generally in the form of parks or urban forests and trees in home gardens, sidewalks, and road medians.

Based on Table 7, the NDVI class that dominates in Malang City is the high greenness class with a percentage of 49.30% and the class with the smallest area is non-vegetation with a percentage of only 0.06%. When based on the NDVI index, the total land area of Malang City that has good vegetation elements at low to very high greenness levels is 77.34%.

However, it should be mentioned that, following the high greenness class, the very low greenness vegetation class has the largest area. In its current state, this class is dominated by residential areas.

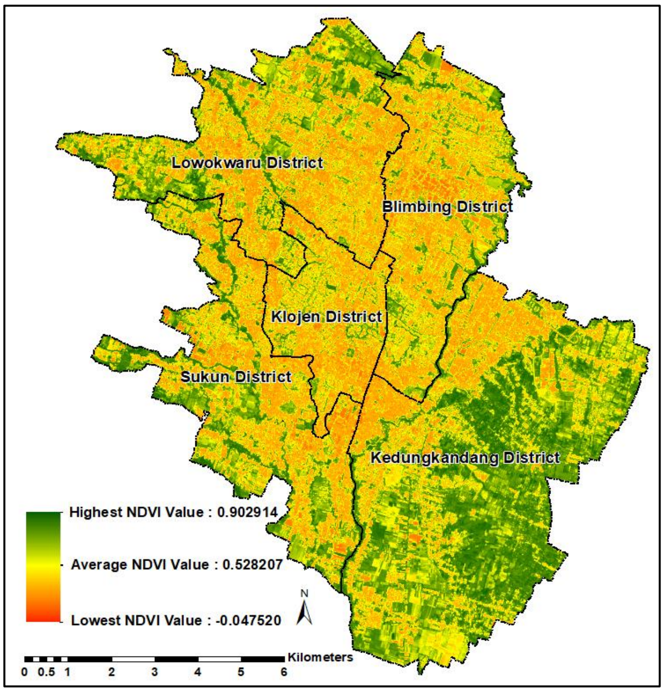

Figure 8. NDVI value of Malang City 2024

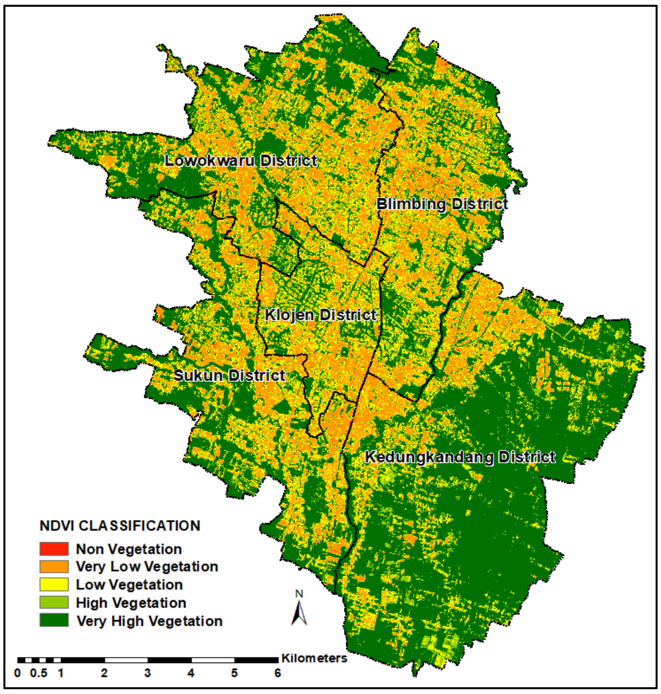

Figure 9. NDVI classification of Malang City 2024

Table 7. NDVI classification area of Malang City 2024

NDVI Class	NDVI Information	Area (km^2)	Percentage (%)
1	Non Vegetation	0.07	0.06
2	Very Low Vegetation	25.08	22.60
3	Low Vegetation	19.10	17.21
4	Medium Vegetation	12.02	10.83
5	High Vegetation	54.72	49.30

Basically, the NDVI distribution condition has the opposite character to the NDBI distribution where when an area has a high NDVI value, the NDBI value will be low and vice versa so that the two indices show a close relationship.

In this case, even though an area has the same land cover characteristics, for example, both have elements of vegetation, the NDVI value at pixels in different areas may be different due to many factors. Among these are those that depend on the kind and state of the vegetation; the older and healthier the vegetation, the higher the NDVI. In contrast, low-density and young plants have reduced chlorophyll levels, which reduces their reflection of greenness [20].

Even though Malang City still has a high greenish NDVI class, which indicates that vegetation is still dominant, the government must still be particularly concerned about this because of the uneven distribution of vegetation components, particularly the limited availability of vegetation in the city's center due to the dense built-up areas, which prevents the artificial and natural elements from coexisting in harmony. In addition, there is also the potential for a decrease in the area of vegetation land in the coming years given the growing population so that the need for land for built-up areas such as residential areas will also increase. This can occur through the conversion of land from non-built to build, so the government needs to think of solutions in meeting the needs of community support but not with land conversion activities that can reduce vegetation land rapidly.

Table 8. Area and average NDVI for each district of Malang City 2024

District	Area (km^2) NDVI Class 1	2	3	4	5	NDVI Value Mean
Blim-bing	0.03	5.3	4.0	2.2	6.1	0.299964
Lowok-waru	0.01	6.8	4.4	2.7	9.7	0.330843
Klojen	0.01	2.9	2.3	1.1	2.2	0.258419
Kedung-kandang	0.01	4.5	4.2	3.6	27.3	0.485447
Sukun	0.02	5.4	3.9	2.1	9.2	0.354993
Total	**0.07**	**25.0**	**19.1**	**12.0**	**54.7**	

Based on Table 8, it is known that the highest average NDVI value is Kedungkandang district, which is 0.485447 and the district with the lowest average NDVI is Klojen district, which is 0.258419. The highest and lowest NDVI averages are related to the extent of vegetation elements in both districts where Kedungkandang district does have the largest area of medium greenness and high greenness NDVI classes compared to other districts with significant numbers. Meanwhile, Klojen district has a larger area in the low NDVI class. This is because the type of land cover in Klojen District is dominated by built-up areas, especially for residential areas, offices, industry so it has a small area of vegetation land which is characterized by low NDVI values.

Through the results of the description of the LST, NDVI, and NDBI conditions that have been carried out, basically, the three variables have a very close relationship where when an area has a high LST value, the NDBI value will also be high while the NDVI value will be low. Conversely, when the LST value is low, the NDBI value will be low and the NDVI value will be high. For instance, Klojen and Kedungkandang districts differ from one another in that Klojen is dominated by built-up areas, whereas Kedungkandang is dominated by vegetated land. As a result, as previously mentioned, the LST, NDVI, and NDBI values of the two districts are opposite. This shows that there are quite significant differences in land use characteristics based on the NDVI and NDBI indices.

3.4 Correlation between NDBI and NDVI on LST in Malang City

Analysis of the relationship between NDBI and NDVI on LST in Malang City was carried out to determine the correlation between these two variables when viewed from visualization in the form of the average LST value and the area of built-up land in each sector. The average land surface area (LST) value for each field is identified using a specific color, and the size of the built-up area in each field is shown by a circle with a corresponding color and radius. This analysis aims to determine the correlation between the two variables on LST descriptively through visual observation. Based on visual observations, the two variables, namely NDBI and NDVI, have a relationship with LST which NDBI is positively correlated and NDVI is negatively correlated. Through the visualization of the comparison of average LST with building area and vegetation, there is a clear continuity between the three variables indicated by the pattern formed in Figure 10. The following is a picture showing the relationship between NDBI and NDVI with LST in Malang City together with its explanation.

Figures 10 and 11 illustrate the correlation between the size of the built-up area and vegetated land and the average LST value calculated using grid. The average LST value on each grid is positively correlated with the area of developed land. A marker circle with a bigger radius up to the maximum is used to encompass the grid with the highest average LST, which is indicated in orange and red. A larger circle radius indicates the area with the largest built-up area. The LST and NDBI relationship is generally positive in nature and is influenced by a number of variables, including vegetation, humidity, air pollution, rock surfaces, dry or wet soil, and diverse artificial materials, among others [34] such as which is shown by the LST-NDBI correlation for Malang City in the figure above. Because more high-capacity and heat-conductive artificial construction materials are used when the built-up area grows, this can have an impact on the LST value [18].

This is in accordance with the analysis results from most studies including Ishola et al. and Prasad et al. in study of Adeyeri et al. [41]. It found that the area with an increase in built-up area, a sign of the addition of urban heat islands, is strongly correlated with the increase in LST. These results are in accordance with research by Morabito et al. [7] that the use of high-resolution built-up area index maps is a useful tool for assessing LST distribution patterns in urban environments.

Meanwhile, for the relationship between the area of vegetated land and LST, there is an inverse pattern between the increase in the average LST and the increase in the area of vegetated land. The distribution of various types of green space over a large area has resulted in the creation of cool areas in parts of the city [42]. Meanwhile, in Malang City, the availability of green space with the largest area. While it is well established that vegetation cover lowers land surface temperatures, different species of vegetation can do so in different ways. The LST value of the average soil temperature beneath trees and shrubs in green spaces is lower than that of the soil temperature beneath summer grass plants [43]. Due to its ability to measure the earth's albedo and affect surface temperature, vegetation is crucial to the Earth's surface. Vegetation is an efficient way to lower UHI because it cools the environment and lowers atmospheric carbon concentrations, which produces carbon dioxide. Vegetation experiences evapotranspiration and provides shade thereby reducing surface and air temperatures [41]. Vegetation creates 15% greater albedo than built-up surfaces because it reflects more longwave radiation and absorbs less heat energy [44]. This shows that a reforestation strategy by planting vegetation also needs to consider the type of vegetation planted by paying attention to the ability of that type of vegetation to regulate the quality of urban microclimate.

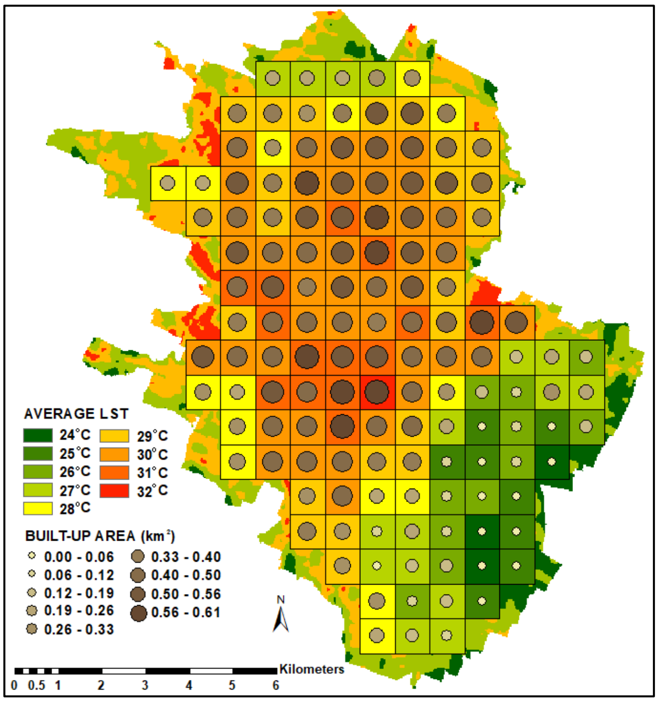

Figure 10. Visualization of LST and NDBI in Malang 2024

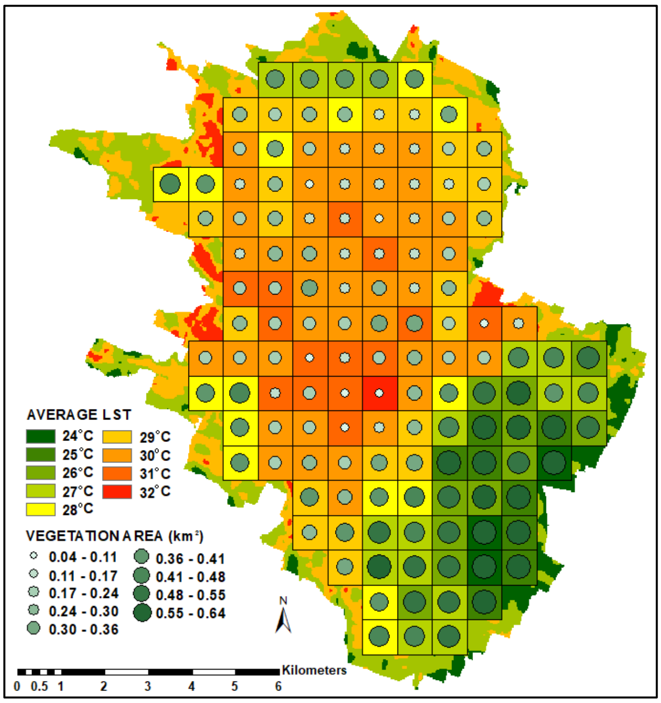

Figure 11. Visualization of LST and NDVI in Malang 2024

3.5 Linear regression analysis

Linear regression methods are commonly used in many studies to obtain information about the relationship between LST and urban landscapes. However, correlation results using regression methods are not always linear due to seasonal variability in land cover data, differences in location, geographic patterns, complexity of landscape structure, and heterogeneity of urban morphology [8].

To calculate correlation using the regression method, the NDVI, NDBI and LST values are extracted from each pixel to calculate the average for each sample unit in the form of a grid.

In the multiple linear regression test, land surface temperature as the dependent variable (Y) and independent variable (X) consists of two, namely vegetation density (X1) and building density (X2). The number of sample grid units entered into the system to obtain the regression model is 1117 grids, where each grid contains data on the average LST value, average NDBI, and average NDVI. The following is the resulting regression model. The results of the classical assumption test on the data compilation in this study are as follows, in Table 9.

a. Coefficient of Determination Test

Table 9. Model summary

Model	R-Square	Adjusted R-Square	Durbin-Watson
1	0.865	0.864	2.055

R-Square of this model is 0.865. And Adjusted R-Square of this model is 0,864. This value including into the strong R-Square category because it is more than 0.670 and shows a good regression model.

b. F/Anova Test

Table 10. Anova test

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	3866.171	2	1933.085	3577.726	0.000
Residual	605.290	1114	0.543		
Total	4471.461	1116			

A value of 0.000 (less than the significance level of 5% or 0.05) was obtained based on the significance results of the F test, in Table 10. This number indicates that all independent variables' effects on LST values can be well explained by the model.

c. T Test

Table 11. Coefficients

Model		Unstandardized Coefficients		Sig.
		B	Std. Error	
1	(Constant)	29.655	0.206	0.000
	X1	11.075	0.695	0.000
	X2	-3.393	0.543	0.000

The partial relationship between variables X and Y is assessed from the T significance test. Table 11 indicates that all variables have a significant impact on the LST values. The multiple linear regression analysis approach produced the model results listed below.

2024: Y (LST) = 29,665 + 11,075 NDBI - 3,393 NDVI

This model has passed the significance test in the form of the F test and T test with an R-Square value of 86.5%. The R-Square value defines that NDVI and NDBI together influence LST by 86.4%. It is possible to define this model by saying that the LST increases with a greater NDBI value and decreases with a higher NDVI value. There is a positive correlation between NDBI and LST, but a negative correlation between NDVI and LST. The following is a graph that shows the relationship of each variable NDBI and NDVI to LST which is calculated using the chart tools in Microsoft Excel.

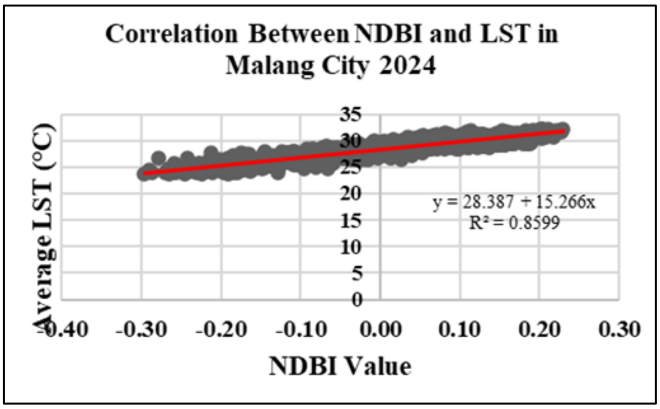

Figure 12. Correlation between LST and NDBI

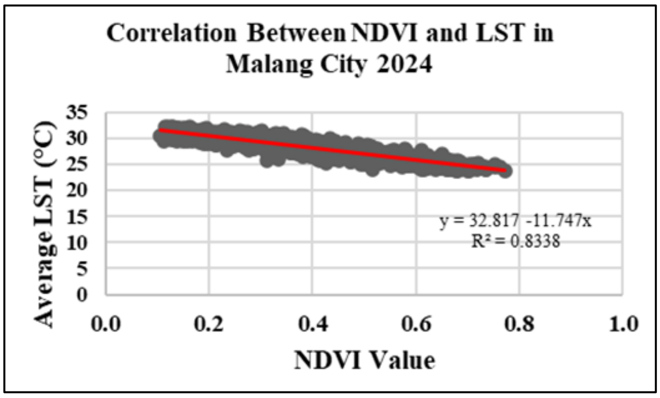

Figure 13. Correlation between LST and NDVI

Based on Figures 12 and 13, the partial influence of each variable on LST is also known. Similar to the previous multiple linear regression model, the signs on the graph indicate a positive coefficient on NDBI and a negative coefficient on NDVI. This indicates that there is, in fact, a significant relationship between LST and building cover, vegetation cover, and watertightness.

NDVI has a significantly negative correlation with LST because there is water content in vegetation, emissions and low albedo in vegetation which can cause a decrease in LST while NDBI has a significantly positive correlation with LST because building and urban materials have high radiant heat and albedo which causes an increase LST [17]. In addition to buildings, often used waterproof materials for urban infrastructure including parking lots, walkways, and bridges also improve heat conductivity [45]. Apart from that, the characteristics of the building can also influence LST where dark building colors with building surface materials that do not reflect light will also result in higher temperatures [46].

Though vegetation cover is known to lower LST, the degree to which different types of vegetation can lower surface temperatures may vary [43]. Therefore, the "greening strategy" in the urban environment should also consider the types of vegetation that are effective in improving air quality and improving the urban microclimate so that it will help create a sustainable city. This shows the complexity in research studies that examine the distribution of LST in urban environments. Apart from that, we also improve urban spatial planning through the preparation of spatial planning documents that take into account the condition of the distribution of buildings and the distribution of vegetation so that future development can be well structured and minimize urban problems that may occur.

3.6 Sustainable policy and planning

The results of this study indicate that there is a significant relationship between building density (NDBI), vegetation (NDVI), and land surface temperature (LST) distribution in Malang City. This finding provides a very strong basis for policy makers to be able to formulate a more environmentally friendly spatial planning policy, which aims to overcome the problem of increasing urban temperatures or Urban Heat Island (UHI).

3.6.1 Policy recommendations for green space development

One of the most important ways to lessen the detrimental effects of urban expansion is to incorporate green spaces into urban areas, particularly in cities like Malang, Indonesia, where high building density and limited vegetation contribute to significant increases in surface temperatures. The implementation of policies that promote the development of parks, urban forests, and green corridors can effectively address the Urban Heat Island (UHI) effect, enhance air quality, and provide recreational opportunities for residents.

Studies reveal that regions with a high concentration of buildings and little greenery undergo significant temperature rises, mainly because of the heat that is absorbed and retained by surfaces made of concrete and asphalt [47]. Increased air pollution, higher energy use for cooling, and negative health effects for urban populations are all possible outcomes of the UHI effect [48]. Therefore, the strategic addition of green spaces is essential for creating a more sustainable urban environment.

The introduction of green spaces serves multiple functions beyond mere aesthetics. Vegetation plays a crucial role in cooling urban areas through the process of evapotranspiration, where plants release moisture into the air, thus lowering surrounding temperatures [49]. For instance, studies have shown that urban green spaces can absorb substantial amounts of heat, significantly reducing surface temperatures during hot weather [50]. Additionally, green spaces improve air quality by filtering pollutants and providing oxygen, contributing to better public health outcomes [51].

Additionally, the creation of parks and urban forests can increase biodiversity and offer habitats for different species, all of which are essential for preserving the ecological balance of urban areas [52]. The presence of green areas also fosters social interactions and community cohesion, as they serve as venues for recreational activities and gatherings.

The effect of the ability of vegetation components in reducing green spaces occurs through the process of increasing albedo or light reflectance which is higher than surfaces not covered by vegetation with the ability to absorb more heat. Therefore, efforts to add vegetation are considered the best solution to reduce temperature. Mitigation design with the development of green spaces is made by considering the distribution of land cover types in areas experiencing the UHI phenomenon [53].

Based on the results of the analysis in Malang City, recommendations in the form of RTH development should be prioritized in areas that have a high percentage of building density and low availability of vegetation components. The district with the highest priority of green space development needs is Klojen district. This is because there is a significant imbalance between the amount of built-up land and vegetated land in Klojen District which is dominated by built-up land. The RTH that can be developed includes improving the quality of existing urban parks and urban forests as well as planting broadleaf trees in the green belt of roads and sidewalks. However, the other four districts still need to improve the quality of existing green spaces and expand green spaces given the increasing population and the potential for continuous land conversion activities in the future.

3.6.2 Environmentally based zoning regulation

The implementation of environmentally based zoning regulations is crucial for urban areas like Malang, Indonesia, where rapid urbanization has led to increased building density and significant temperature variations. By utilizing Land Surface Temperature (LST) and Normalized Difference Built-up Index (NDBI) data, city governments can develop zoning policies that effectively manage land use while promoting environmental sustainability. This approach not only addresses the Urban Heat Island (UHI) effect but also encourages the creation of green spaces and the use of eco-friendly building materials.

Due to the heat absorption and retention properties of impermeable surfaces, high building density areas frequently experience increased temperatures. Research indicates that implementing zoning regulations that require the maintenance or creation of green spaces in these areas can significantly reduce ambient temperatures [54]. By mandating green roofs, parks, and urban forests, cities can leverage the cooling effects of vegetation, which is essential for improving urban microclimates [55].

The integration of LST and NDBI data into zoning regulations allows for a more informed approach to urban planning. LST data provides insights into temperature variations across different urban areas, while NDBI helps identify built-up regions. This information can guide policymakers in zoning decisions, ensuring that areas with high temperatures are prioritized for green space development [56]. For example, studies have shown that areas with higher NDVI (Normalized Difference Vegetation Index) correlate with lower LST, highlighting the importance of vegetation in urban environments [57].

Environmentally based zoning can also promote the use of heat-reflective and eco-friendly building materials. By establishing guidelines that encourage the use of such materials in high-density areas, cities can reduce heat absorption and improve energy efficiency in buildings [58]. This not only contributes to lower energy consumption but also enhances the overall sustainability of urban development.

3.6.3 Integration of sustainable planning into urban planning

The integration of sustainable planning into urban development is essential for addressing the multifaceted challenges posed by rapid urbanization, climate change, and environmental degradation. In cities like Malang, Indonesia, effective urban planning must incorporate policies related to urban temperature control alongside other environmental policies, such as stormwater management and air quality improvement. Utilizing indicators such as LST, NDBI, and NDVI can significantly enhance the government's ability to monitor and manage the impacts of urban development.

A comprehensive strategy that takes into account the relationships between different environmental conditions is necessary for sustainable urban design. For instance, integrating temperature control measures with stormwater management can help mitigate flooding while simultaneously reducing urban heat [59]. This holistic perspective is crucial for creating resilient urban environments that can adapt to climate change.

The application of indicators such as LST, NDBI, and NDVI provides valuable data for urban planners. LST can help identify areas experiencing extreme heat, while NDBI can indicate the extent of built-up areas, and NDVI can assess vegetation cover [60]. By analyzing these indicators, planners can make informed decisions about where to implement green infrastructure and other sustainability measures.

Policies that promote the integration of vegetation into spatial planning—such as planting trees along sidewalks, creating vertical gardens, and installing green roofs—can significantly enhance urban resilience. These green solutions not only help to cool urban areas but also improve air quality and manage stormwater runoff effectively [61]. Urban greenery can reduce surface temperatures and improve overall urban livability.

3.6.4 Data-based urban development

The integration of data-driven planning policies is essential for addressing the increasing temperatures in Malang City, which are closely linked to the conversion of green areas into built-up spaces. By adopting satellite monitoring techniques that utilize indicators such as LST, NDVI, and NDBI, the city government can make informed decisions that promote sustainable urban development. This approach not only allows for the prediction of development impacts but also facilitates the planning of new environmentally friendly areas that maintain a balance between built-up zones and green spaces.

Utilizing LST, NDVI, and NDBI data enables city planners to predict the potential impacts of urban development on local temperatures and environmental quality. For instance, LST data can highlight areas experiencing extreme heat, while NDVI can indicate the health and distribution of vegetation [62]. Such predictive capabilities are crucial for implementing timely interventions before temperature increases become critical.

The continuous monitoring of urban dynamics through satellite imagery provides valuable insights into how urbanization affects environmental conditions. Research has demonstrated that combining data from multiple sources, such as LST and NDVI, might be a useful way to evaluate how well urban development and ecological surroundings are coordinated [63]. This information can guide policymakers in making adjustments to urban planning strategies to mitigate adverse effects.

Data-driven approaches can facilitate the strategic planning of green spaces within urban areas. Planners can determine where new parks, green roofs, or tree planting efforts are needed by examining regions with a high building density and little vegetation cover. In order to improve the general quality of life for inhabitants and strengthen urban resilience against climate change, proactive planning is important.

4. CONCLUSIONS

This research conducted a detailed analysis of the spatial distribution of LST and its correlation with the NDBI and NDVI in Malang City. The study's findings show that while NDVI and LST have a negative correlation, NDBI and LST have a positive correlation. This suggests that urbanization, which is defined as the growth of Malang City's built-up area, significantly contributes to surface temperature rise, although higher vegetation density mitigates this effect.

Quantitative analysis using multiple linear regression models revealed that NDBI and NDVI together explain 86.4% of the variation in SST (R^2 = 0.864), indicating a strong relationship between land cover and surface temperature. Specifically, the regression model shows that an increase in NDBI by 0.1 results in an increase in SST of 1.075℃, while an increase in NDVI by 0.1 results in a decrease in SST of 0.339℃. This underlines the important role of vegetation in reducing urban heat and highlights the negative impacts of dense urban development on local temperatures.

Further spatial analysis reveals that in 2024, the average LST of Malang City is 28.32℃, with the highest temperature exceeding 34.64℃ in densely populated residential areas, especially in Klojen District. In contrast, districts with higher vegetation cover, such as in Kedungkandang, show a lower average LST value of 26.86℃, reflecting the cooling effect of green open spaces. The findings show that very high temperatures (above 30.2℃) dominate 23.38% of Malang City, especially in the city center, while low temperatures (below 25.2℃) only cover 10.61%, mostly in the suburbs of Malang City which have abundant vegetation.

These findings highlight the necessity of Malang City's sustainable urban development strategy in order to mitigate the Urban Heat Island (UHI) effect. Rapid urbanization, marked by a 51% increase in built-up areas from 2012 to 2020, has led to significant environmental challenges, including higher surface temperatures. To mitigate these impacts, policy interventions should prioritize the creation of urban green spaces, such as parks, green corridors, and urban forests, especially in densely populated residential areas in Malang City. These green infrastructures can reduce temperatures through evapotranspiration and shading, improving the city’s microclimate and overall livability.

In addition, this study suggests the implementation of environmentally-based zoning regulations that require the integration of green spaces in high-density urban zones. Zoning regulations should also promote the use of sustainable building materials with lower heat absorption functions that aim to reduce surface temperatures in built-up areas in Malang City.

In conclusion, the application of remote sensing and geospatial analysis in this study provides valuable insights into the existence of a relationship between urban expansion and environmental conditions in Malang City. By leveraging satellite-based data such as LST, NDBI, and NDVI, policymakers can make informed decisions to develop environmentally sustainable urban plans. This strategy will be critical to balancing future urban growth with the need to maintain a healthy environment and mitigate the adverse impacts of urbanization on the local climate.

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