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RESEARCH ARTICLE

# Analysis of The Effect of Land Use Change Using Random Forest Algorithm on Surface Temperature and Its Relationship With Urban Heat Island Phenomenon

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**Abstract**

Bandar Lampung City is one of the cities experiencing rapid population growth. Its strategic location for development and infrastructure has made it a prime target for urbanisation. This urbanisation process has increased built-up land areas and surface temperature, triggering the emergence of the urban heat island (UHI) phenomenon. This study aims to analyse land use changes and surface temperature to determine the spatial distribution of the urban heat island phenomenon in Bandar Lampung City using Landsat 8 remote sensing data. The analysis was carried out through several extraction stages, one involved examining land use changes using the random forest algorithm as an ensemble learning method to address classification problems. The classification results showed an accuracy level of 85%, with the most significant changes occurring in built-up and vegetated areas. The shift in land function from natural or vegetative conditions to built-up areas such as residential zones, commercial areas, and urban infrastructure is driven by population growth and increased economic activity. This transformation has resulted in reduced green spaces and agricultural land, increased surface temperature, decreased groundwater absorption capacity, and intensified the urban heat island phenomenon, affecting ecosystem balance and urban environmental comfort. Based on data processing results, the average surface temperature distribution in 2013 and 2023 was 22.62°C and 26.65°C, respectively, with the UHI distribution increasing by 762.95 hectares.

**Keywords:** Land Use, Random Forest, Surface Temperature, Urban Heat Island

## 1. Introduction

Urban development and population growth are two inseparable aspects of the dynamics of metropolitan areas. As centers of economic, social, and government activities, cities attract population migration from rural areas, which has implications for increasing the need for built-up land and pressure on the environment (Urfiyah, 2019) (Riza Fadholi Pasha, Sheily Widyaningsih, 2014). This phenomenon reduces green open space (RTH) and converts natural land into built-up areas, which increases land surface temperature (LST) and triggers the urban heat island (UHI) phenomenon (Taufiq Ramadhan et al., 2023) (Sunyari, 2022). UHI not only disrupts temperature comfort in urban areas but also worsens air quality and increases energy use due to excessive air conditioning (Badan Pusat Statistik, 2024).

The Central Bureau of Statistics (2023) reported that the population of Bandar Lampung City reached 1,100,110, accompanied by an annual growth rate of 0.655%. This growth is attributed to the city's strategic position as a link between Java and Sumatra, as well as the presence of educational institutions like the Sumatra Institute of Technology (ITERA). (Qamilah et al., 2020) (Qamilah et al., 2020). Population growth is accompanied by land conversion, with the area of settlements increasing by 18.6% over the last ten years (Muhammad & Muta'ali, 2018). As a result, the city's surface temperature rose from 23.12°C (2011) to 33.03°C (2019), with land use change accounting for 48% of the increase (Canggah Abiyyu Ali'in Saputri, 2021). This condition is worsened by climatic factors such as the El Niño phenomenon, which causes daytime temperatures to reach 37.8°C (Arifah & Susetyo, 2018).

Previous studies have identified the correlation between land use change and UHI using remote sensing technology. Landsat satellite imagery, for example, has proven effective in mapping LST and vegetation dynamics through indices such as NDVI (Normalized Difference Vegetation Index) (Saputra, 2023). However, most studies still rely on conventional classification methods with limited accuracy. On the other hand, the Random Forest (RF) algorithm offers higher accuracy (OA: 93.37%; kappa: 0.86) in land classification by utilizing multi-temporal and multi-spectral data (Reay et al., 2007). Integrating RF with cloud computing platforms such as Google Earth Engine (GEE) enables efficient analysis of petabytes of data, including LST extraction and real-time land change monitoring (Nurhuda et al., 2019) (Taufiq Ramadhan et al., 2023).

By utilizing remote sensing and GIS technologies to identify the impact of land use changes due to increased land surface temperature (LST), the researcher aims to investigate how these changes, analyzed using the Random Forest algorithm, affect residential temperatures and the Bandar Lampung City Heat Island phenomenon. Utilizing a Cloud Computing Platform will help achieve the research goal of providing a spatial and temporal overview of the Bandar Lampung City Heat Island phenomenon.

## 2. Material and Method

### 2. 1. Data and Research Locations

This research was conducted in Bandar Lampung City, located at the coordinates of 5°20' - 5°30' South latitude and 105°28' - 105°37' East longitude, covering an area of 197.22 km$^2$ (Badan Pusat Statistik, 2024) (Figure 1). Topographically, the region consists of coastal areas, hills, highlands, and small islands, with an altitude variation of 0 to 700 meters above sea level (masl). These geographical characteristics significantly affect environmental dynamics, particularly land use change and surface temperature distribution.

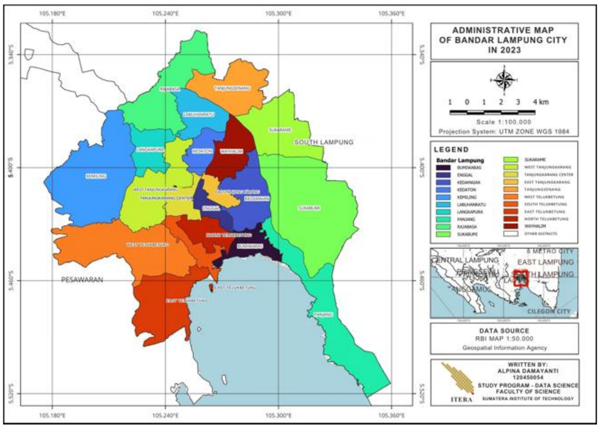


Fig 1. Research Location

The research data consisted of primary and secondary data. Primary data were obtained through field observations using the GPS MAP Camera application for mapping land use change and Thermometer-Hygrometer to measure land surface temperature (in-situ), as well as visual documentation at sample points that experienced significant changes in Land Surface Temperature (LST). Secondary data included Landsat 8 ToA (Top of Atmosphere) Reflectance Collection 2 Tier 1 satellite images for 2013 and 2023 accessed through Google Earth Engine (GEE) and administrative boundary vector data in shapefile (.shp) format from the Geospatial Information Agency (BIG) through the Indonesian Homeland Portal (https://tanahair.indonesia.go.id).

### 2. 2. Research Metod and Stage

A systematic workflow consists of several stages of data processing utilized in this study (Figure 2). During this process, land use classification and surface temperature calculations were conducted to generate the Urban Heat Island (UHI) analysis parameters for Bandar Lampung City.

This study used data from Landsat 8 images obtained through the United States Geological Survey (USGS) website and processed using the Google Earth Engine platform. Data pre-processing was performed to remove noise, including scaling, cloud masking, cropping the study area, and RGB (Red, Green, Blue) band compositing using Bands 1-5 and Band 7 in a combined band order of 432. Additionally, Band 10 was employed to calculate the land surface temperature (LST).

#### 2. 2. 1. Random Forest Classification

The labeling process is done with polygon features to determine five land use categories, namely Water Bodies, Built-up Land, Vegetated Land, Agricultural Areas, and Open Land. Each category is displayed with a different color as the basis for classification. To overcome the imbalance in the number of samples between classes, oversampling was performed using the *oversampleClass* and *maxCount* functions on Google Earth Engine, so that the distribution of samples between classes becomes balanced and reduces bias in the classification model.

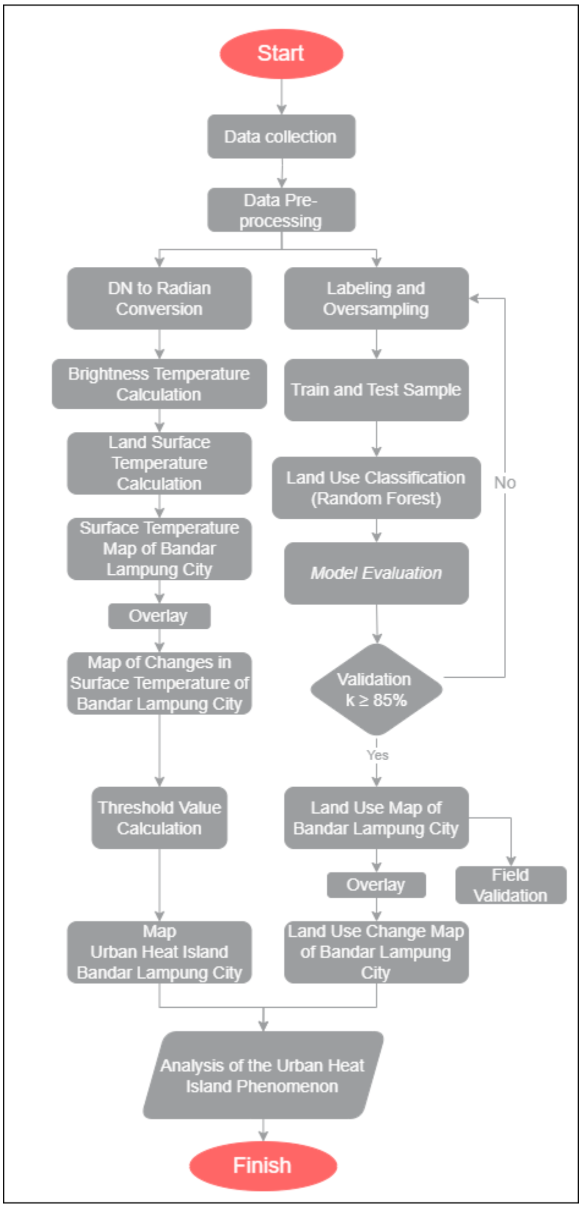


Fig 2. Research Flow Chart

The dataset was divided into two subsets: training data (80%) and testing data (20%), using a stratified sampling approach. This approach ensures that the data distribution in the subsets remains proportional to the original class distribution, thus avoiding bias in training the classification model.

Random Forest (RF) algorithm was used to build the land use classification model. This algorithm was chosen for its ability to overcome overfitting through bootstrap aggregating (bagging) and random feature selection techniques. The input variables used include the seven spectral bands of Landsat 8, while the target variables are the predefined land use classes. The main parameters optimized in the RF model include numberOfTrees, minLeafPopulation, and bagFraction. The prediction results from the RF model were combined using the Majority Voting method to produce a more stable and accurate final class label (Pal, 2005) (Figure 3).

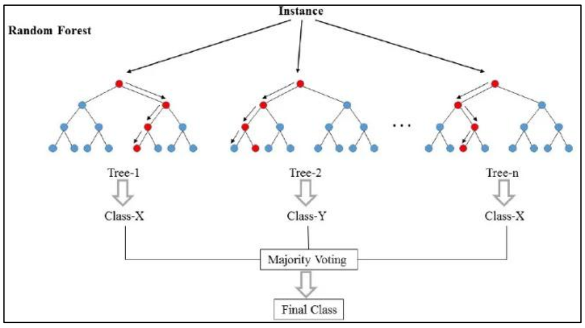


Fig 3. Random Forest (Marlina, 2022)

Evaluation of classification accuracy is done by comparing the reference class (test data) and classification results using a confusion matrix (Table 1). This method produces two main parameters: Overall Accuracy (OA) to measure the overall percentage of correct classifications, and the Kappa Coefficient to assess the fit between predictions and actual data. Based on the Kappa Coefficient Interpretation Table, the model is declared valid if it achieves OA and Kappa Coefficient ≥85% (Anthony J. Viera, 2005) (Table 2). If the evaluation results do not meet the criteria (No), model recalibration is carried out through the addition of training samples. If it meets (Yes), the classification results are forwarded to the final land use map creation stage. The Kappa accuracy test can be written systematically which is expressed by the following equation (Wibowo, T.W., Danoedoro, 2010):

Table 1. Confussion Matrix

| Reference data | Classified into classes (class data on map) | | | | | Count | Producer's Accuracy |
|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | | |
| A | $x_{ii}$ | | | | | $x_{i+}$ | $\frac{x_{ii}}{x_{i+}}$ |
| B | | | | | | | |
| C | | | | | | | |
| D | | | | | | | |
| E | | | | | | | |
| total column | $x_{+i}$ | | | | | | |
| User's Accuracy | $\frac{x_{ii}}{x_{+i}}$ | | | | | | |

$$User\ accuracy = \frac{x_{ii}}{x_{+i}} \times 100\% \quad (1)$$

$$Producer\ accuracy = \frac{x_{ii}}{x_{i+}} \times 100\% \quad (2)$$

$$Overall\ accuracy = \frac{\sum_i x_{ii}}{N} \times 100\% \quad (3)$$

$$Kappa\ accuracy = \frac{N \times \sum_{i=1}^{I} x_{ii} - \sum_{i=1}^{I}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{I}(x_{i+} \times x_{+i})} \quad (4)$$

with x_ii is pixels on the main diagonal (correct classification) confusion matrix, x_(i+) is the total number of pixels in a column in a row, x_(+i) is the total number of pixels in a column, and N is the total number of sample pixels in the confusion matrix.

Table 2. Interpretation of Kappa Coefficient Values

| Kappa Coefficient Value | Interpretation of Kappa Value |
|---|---|
| $0 <$ | Poor |
| $0{,}01 < 0{,}20$ | Slight |
| $0{,}21 < 0{,}40$ | Fair |
| $0{,}41 < 0{,}60$ | Moderate |
| $0{,}61 < 0{,}80$ | Substantial |
| $0{,}81 < 0{,}99$ | Almost Perfect Agreement |

Overlay is a combination or overlapping of various geographic layers to obtain new data. overlay is done to see changes in land use in 2013 and 2023.

### 2. 2. 2. Urban Heat Island

Urban Heat Island (UHI) is a condition in which the air temperature in a city is hotter than the surrounding area. This phenomenon occurs because urban surfaces such as asphalt and concrete absorb solar heat during the day and then release it gradually at night, making the air feel hotter. Using air conditioners and electrical devices to cool buildings exacerbates the UHI by increasing heat emissions (Kawamuna et al., 2017).

To comprehend the Urban Heat Island (UHI) phenomenon, land surface temperature (LST) acts as a vital indikator (Bahavira *et al.*, 2025). LST represents the temperature measured at the Earth's surface and its increase results from the reduction of green spaces and the rise in the number of buildings in urban areas (Zhao et al., 2022). Analyzing LST helps to illustrate the relationship between environmental changes, such as residential development, and local warming (Srivastava & Ahmed, 2023). The UHI threshold can be established by calculating the specific LST values using the following formula (Sejati et al., 2019):

Using data from the Landsat 8 thermal band and OLI Band 10, convert the digital numbers (DN) to spectral radiance values using the formula Equation 5.

$$L_\lambda = ML \cdot Q_{cal} + AL \quad (5)$$

with Lλ is TOA(Top of Atmoshpere) Spectral Radiance in watts/(meter squared*ster* µm), ML is radiance_mult_band_10, AL is radiance_add_band_10, and Qcal is digital number.

The LST value is calculated using the Planck algorithm, as shown in Equation 6. The LST value is the temperature value in Kelvin units.

$$T = \frac{K2}{\ln\left(\frac{K1}{L_\lambda}\right) + 1} \quad (6)$$

with T is brightness temperature (K), K1 is k1_constant_band_10, and K2 is k2_constant_band_10. The brightness temperature T obtained can be converted into degrees Celsius using the formula Equation 7.

$$T_{Celcius} = T - 273.15 \quad (7)$$

with $T_{Celcius}$ is LST temperature in degrees Celsius, T is LST temperature in degrees Kelvin, and 273.15 is Conversion constant from Kelvin to Celsius.

Surface temperature data is selected based on the UHI threshold. The determination of the UHI threshold value can be calculated using the steps in Equations 8 and 9 (Seprila Putri Darlina , Bandi Sasmito, 2018).

$$Threshold\ Limit\ Value = (\mu + 0.5\alpha) \quad (8)$$

$$UHI = LST - (\mu + 0.5\alpha) \quad (9)$$

with μ is average Land Surface Temperature (LST) and α is Standard deviation value of Land Surface Temperature (LST). Based on previously established threshold calculations, the Urban Heat Island (UHI) phenomenon can be classified according to its level of spread (Table 3).

Table 3. UHI Distribution Classification

| Class | UHI Value |
|---|---|
| Non UHI | $< 0°C$ |
| UHI 1 | $0 - 2°C$ |
| UHI 2 | $2 - 4°C$ |
| UHI 3 | $4 - 6°C$ |
| UHI 4 | $6 - 8°C$ |
| UHI 5 | $> 8°C$ |

## 2. 3. Field Validation

The data validation process in the field was conducted using a GPS Map Camera to record the coordinates of the sample locations and a Thermometer-Hygrometer to measure the temperature. The number of samples was determined using the Slovin formula (Dev Roy & Trivedi, 2023). To ensure data accuracy with a minimum margin of error. Based on mapping standards, the minimum number of samples used is 30 points for areas with a scale of 1:50.000 to represent the full variation of land conditions (Table 4).

Table 4. Number of Sample Points Based on Scale

| Scale | Density Class | Minimal Plot | Minimum Sample Total (MST) |
|---|---|---|---|
| 1:25.000 | 5 | 30 | 50 |
| 1:50.000 | 3 | 20 | 30 |
| 1:250.000 | 2 | 10 | 20 |

$$A = MST + \left(\frac{Area\ (Ha)}{1500}\right) \quad (10)$$

Where A is Minimum number of samples, and MST Minimum Sample Total.

The following are the results of the ground check in Table 8 by obtaining 30 sample points from the calculation of the scale area of the research area map. The results of the ground check map in (Figure 4) have a scale of 1: 100.000 which results in a minimum plot of 15 points and a total sample of at least 25 points. From previous research, researchers concluded to take 30 sample points from the same scale value (Pramitha, 2023).

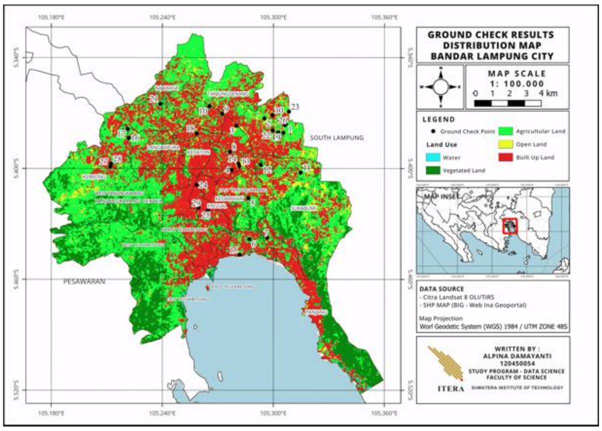


Fig 4. Field Data Validation Map

## 3. Result and Discussion

### 3. 1. Land Use Classification

Land use classification in Bandar Lampung City uses Landsat 8 satellite images (2013 and 2023) with a combination of red, green, blue (RGB) colors to facilitate visual observation of differences in land types (Figure 5). The Random Forest algorithm was run on the Google Earth Engine (GEE) platform with customized default settings to make the calculation process faster and more accurate. The 2013 and 2023 evaluation results showed that the model was very reliable with an overall accuracy rate of 94.7% and 97% as well as a classification result suitability of 93.2% and 96.2%, meaning that almost all land categories were correctly identified (Anthony J. Viera, 2005).

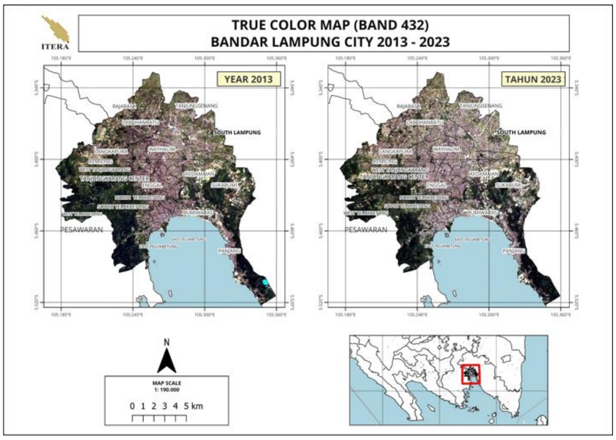


Fig 5. Band Combinations

In 2013, agricultural land dominated land use in Bandar Lampung City with an area of 8,111.839 Ha (41.12%), followed by built-up land of 6,360.209 Ha (32.24%). Kemiling sub-district has the highest agricultural area (1,289.52 Ha), while Sukabumi sub-district dominates built-up land (501.21 Ha).

Throughout the decade, there was a decrease in agricultural land to 7,952.297 Ha (40.31%) and an increase in built-up land to 7,010.963 Ha (35.54%) in 2023. Kemiling sub-district remains the largest contributor of agricultural land (1,256.94 Ha), while Sukabumi sub-district experienced the largest expansion of built-up land (614.88 Ha).

Significant changes also occurred in open land which decreased by 7.92% (1,562.47 Ha) and vegetated land which increased by 5.6% (1,105.5 Ha) (Figure 6). These changes illustrate the rapid development of the city which has led to the shrinkage of agricultural land and open land.

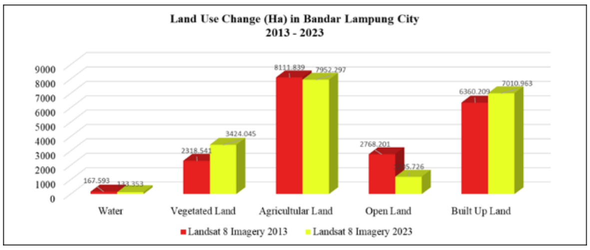


Fig 6. Graph of Land Use Change (Ha) in 2013 and 2023

The classification map (Figure 7) divides the region into five land types: water (blue), vegetated land (dark green), agricultural land (light green), open land (yellow), and built-up land (red). In red, built-up land is concentrated in the city center, while green land is increasingly shifting to the suburbs. The reduction of green land and the increase of built-up areas, such as asphalt and concrete, can significantly raise the surface temperature of the land, triggering the formation of urban heat islands.

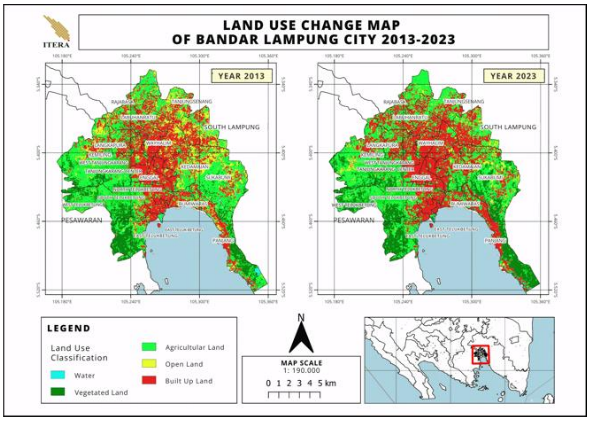


Fig 6. Land Use Classification

### 3. 2. Land Surface Temperature (LST) Changes

Based on the results of Landsat 8 Collection 2 Tier 1 Raw Scene image data processing in 2013, the surface temperature in Bandar Lampung City in 2013 was dominated by the 21-24°C class (7,275.6 Ha; 37.1%) with an average temperature of 23.45°C, reflecting the relatively cool environmental conditions due to the dominance of agricultural land and open space (Figure 7).

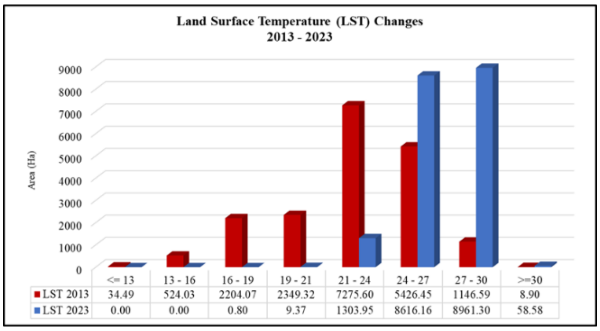


Fig 7. Land Surface Temperature (LST) Change Graph 2013 and 2023

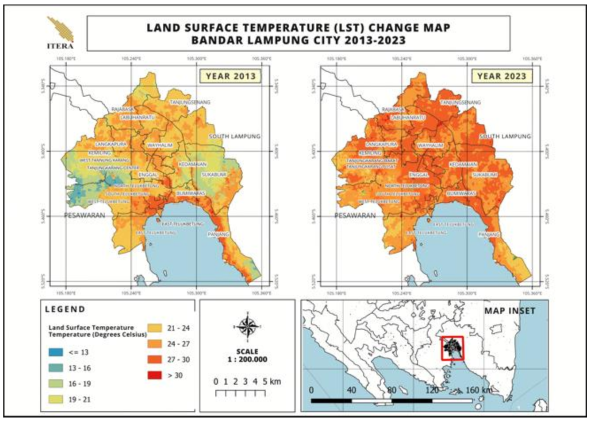


Fig 8. Land Surface Temperature

Sukabumi sub-district has the largest area in the 19-21°C class (828.64 Ha), while South Teluk Betung recorded the highest temperature (27-30°C) covering 157.16 Ha (Figure 8). However, by 2023, there is a significant shift to the 27-30°C class (8,961.3 Ha; 45.7%) with an average temperature of 25.65°C and a maximum of 32.46°C (Figure 7). Sukabumi sub-district experiences an extreme increase in this class (1,492.75 Ha), driven by land conversion to settlements and infrastructure (Figure 8).

The 2013-2023 LST change is characterized by a decrease of 5,971.66 Ha in the 21-24°C class and an increase of 7,814.70 Ha in the 27-30°C class (Table 5). The average temperature increased by 2.2°C, as agricultural land shrinks (-1,159.54 Ha) and built-up land expands (+948 Ha).

Table 5. LST Area (Ha) and Change in 2013 and 2023

| LST Classification (°C) | LST Area (Ha) | | Change (Ha) | Information |
|---|---|---|---|---|
| | Year 2013 | Year 2023 | | |
| ≤ 13 | 34.49 | 0.00 | 34.49 | Fixed |
| 13 – 16 | 524.03 | 0.00 | 524.03 | Fixed |
| 16 – 19 | 2204.07 | 0.80 | 2203.27 | Changing |
| 19 – 21 | 2349.32 | 9.37 | 2339.95 | Changing |
| 21 – 24 | 7275.60 | 1303.95 | 5971.66 | Changing |
| 24 – 27 | 5426.45 | 8616.16 | 3189.71 | Changing |
| 27 – 30 | 1146.59 | 8961.30 | 7814.70 | Changing |
| ≥ 30 | 8.90 | 58.58 | 49.68 | Changing |

Urban areas such as Sukabumi and Teluk Betung Barat have become the epicenter of rising temperatures due to the loss of heat-absorbing vegetation and the expansion of impervious surfaces (Pramitha, 2023). This pattern is further emphasized by global warming trends observed in tropical regions, with the spatial distribution of land surface temperature (LST) illustrated on the change map (Figure 8) (Yumna & Muhamad, 2020).

### 3. 3. Analysis of Urban Heat Island Phenomenon

Urban Heat Island (UHI) in Bandar Lampung City was analyzed using threshold values calculated from the average Land Surface Temperature (LST) and standard deviation. The UHI threshold increased from 24.18°C (2013) to 27.46°C (2023), indicating the influence of rising surface temperature and land use change on UHI intensity (Table 6).

Table 6. Average Surface Temperature, Standard Deviation, and Threshold Values 2013 and 2023

| Year | Avg LST | StdDev | Threshold Value |
|---|---|---|---|
| 2013 | 22,6264 | 3,1093 | 24,1811 |
| 2023 | 26,6515 | 1,6087 | 27,4559 |

The UHI-affected area increased from 31.37% (5,950.93 Ha) in 2013 to 35.43% (6,713.88 Ha) in 2023 (Table 7). However, this increase is relatively moderate due to the high value of the LST digital number and standard deviation that affect the threshold for defining UHI areas, resulting in non-UHI areas remaining dominant (Fawzi, 2017).

Table 7. Non UHI and UHI Areas 2013 and 2023

| Year | Non UHI | | UHI | |
|---|---|---|---|---|
| | (Ha) | (%) | (Ha) | (%) |
| 2013 | 13.018,52 | 68,63 | 5.950,93 | 31,37 |
| 2023 | 12.236,27 | 64,57 | 6.713,88 | 35,43 |

The UHI epicenter in 2023 is concentrated in areas with residential density and industrial activities, such as Sukabumi and East Teluk Betung sub-districts, which have temperatures ≥30°C. In contrast, suburban areas like Kemiling tend to have lower temperatures (16-19°C) due to the presence of remaining vegetation cover (Figure 9). The main contributors to the increase in UHI include the prevalence of impermeable materials such as asphalt and concrete, high building density, and human activities that trap heat (Fawzi, 2017) (Senanayake et al., 2013).

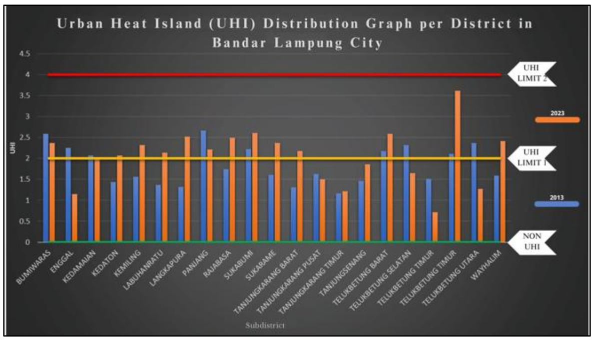


Fig 9. Urban Heat Island (UHI) Distribution Graph per Sub-District

In 2023, UHI centers were identified in regions marked by dense industrial and residential land use. These areas include the Sukabumi, Tanjung Senang, and Kemiling sub-districts, which account for 3-13% of the city's total area (Figure 10). In contrast, areas with high vegetation cover in the Kemiling sub-district exhibited lower temperatures, confirming the role of vegetation in reducing heat through evapotranspiration mechanisms (Senanayake et al., 2013).

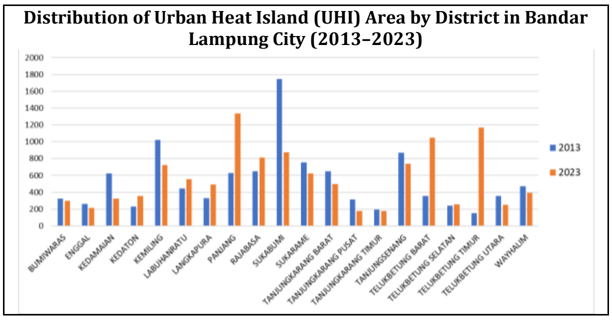


Fig 10. Urban Heat Island (UHI) Area Graph per Sub-District

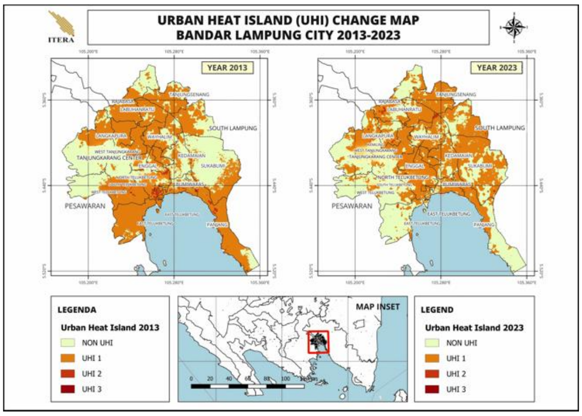


Fig 11. Urban Heat Island

Based on this research, efforts to address the urban heat island phenomenon include increasing vegetation density in areas with high temperatures. This is important because areas with high surface temperatures generally have very little vegetation compared to suburban areas (Figure 11). Previous research analysed the relationship between land cover and vegetation density on surface temperature to spatially identify the urban heat island phenomenon in Bandar Lampung (Qamilah *et al.*, 2020).Therefore, the government needs to implement environmentally oriented spatial planning strategies, such as increasing green open spaces, maintaining existing vegetation areas, and regulating the spacing and height of buildings to reduce surface temperatures and create a cooler and more sustainable urban climate.

## 4. Conclusion

This study confirmed an increase in surface temperature (SST) in Bandar Lampung City from 22.62°C (2013) to 26.65°C (2023), driven by the conversion of agricultural land and open space into dense settlements (+3.3%). Random Forest classification based on Google Earth Engine (97% accuracy) identified Urban Heat Island (UHI) area expansion of 4.06% (762.95 Ha), concentrated in urban areas such as Sukabumi and East Teluk Betung. The 5-10°C temperature difference between urban centers and suburbs confirms the role of vegetation in heat mitigation. These results confirm the effectiveness of remote sensing and Geographic Information Systems (GIS) in environmental monitoring, with implications for sustainable spatial policies. This UHI phenomenon results in reduced thermal comfort for residents, increased energy consumption for cooling, and worsened air quality and health, especially for vulnerable groups such as children and older people. Furthermore, rising urban temperatures also accelerate environmental degradation and exacerbate local climate change. Therefore, sustainable spatial planning policies are needed, including expanding green open spaces, preserving vegetation, and controlling building density to mitigate the impact of heat and maintain urban environmental balance.

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