Analysis of urban heat island intensity using multi temporal landsat data; case study of Kendari City, Indonesia

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Abstract. The urban air temperature has gradually increased in almost all cities in the world, including Kendari City. This is indicated by the increase in building materials and reduced vegetation biomass in urban areas that have consequences of increasing surface temperatures and forming a micro-climate phenomenon called urban heat island (UHI). The aim of this study is to analyse of UHI intensity in Kendari region for the periods 2001-2014-2019, based on the distribution of land surface temperature (LST), which was analysed through thermal infrared (TIRS) and operational land imager (OLI) sensors onboard Landsat-7 and Landsat-8, each image has an atmospheric correction and brightness temperature. The results show the intensity of UHI during the 2001 to 2014 period increased by 2.44 °C, while in 2019 the intensity decreased by 2.27 °C from the previous period. These fluctuations are closely related to the land cover (LC) changes especially in built-up areas, vegetation, and bare soil as the effects of the urbanization process, and parameters of the normalized difference vegetation index (NDVI).

1. Introduction
The majority of the global population growth is currently in urban areas. It is noted that in 2018 the urban population is around 55% of the world population and is estimated to increase to 68% in the year 2050 or around 2.5 billion people [1]. Global urbanization rates has increased by 21% over the past 60 years [2]. During the same period, global average temperatures are projected to rise by between 1.3 and 1.8 °C in response to anthropogenic atmospheric warming [3]. Urbanisation leads to rapid constructions, which use low albedo materials leading to high heat absorption in urban area besides reduced vegetation cover area [4]. Land cover (LC) changes and the presence of new material on urban surfaces such as concrete, asphalt, tiles, and other materials then joins the emission of heat, humidity and pollutants to dramatically change the surface temperature of the atmosphere to be hotter [5], therefore urbanization is considered the most important factor causing climate change [6].

In line with the above, other problems that occur in cities other than global issues are also the problems of microclimate. This climate is referred to as Urban Heat Island (UHI), which is defined as a phenomenon of urban temperatures around 2-5 °C higher than the surrounding rural areas [7]. The UHI
effect in some cases can even be higher than 10 °C from the temperature of a non-urban area [8]. Under optimum conditions, UHI can increase up to 10-15 °C [9]. The increasing urban temperatures are caused by the presence of urban structures and infrastructure materials. Urban structures and materials change land cover geometry and irradiative properties such as albedo and emissivity [3], [10], and such matters are closely related in influencing the magnitude of UHI intensity in an urban area.

The development of remote sensing technology for researchers has provided much convenience in conducting UHI studies on a global scale. At present, the use of thermal infrared bands is important for research related to UHI [6], especially its measurement of Land Surface Temperature (LST), as the main parameter of the dynamics of the urban thermal environment [11]. Researchers often used satellite images (e.g. thermal bands of Landsat TM/ETM+/OLI) to derive the surface UHI effect. It is measured by calculating the difference of land surface temperature (LST) between urban/built-up and non-urban areas (e.g. waterbody and vegetation areas) [12].

The potential of UHI in urban areas is very significant, not least in Kendari City as the capital city of Southeast Sulawesi Province, where population growth and development activities increase rapidly each year. The density of Kendari City residents in 2017 reached 1,364 people/km² with a projected population of 370,728 inhabitants, the land area of which was 271.76 km² or about 0.7% of the area of Southeast Sulawesi Province [13]. Until now, Kendari City does not yet have information describing the spatial pattern and intensity of UHI, and this is the reasons for this research. Based on this context, the objectives of this research are to; (1) map UHI in period 2001, 2014 and 2019 in Kendari City (these three sub-scene images are chosen to differentiate the LC changes over a period of 18 years or to obtain the massive change condition), (2) relate UHI to land cover patterns, and (3) analyse UHI based on the magnitude of its intensity.

2. Methods

2.1. Study area

The city of Kendari, the capital of Southeast Sulawesi, Indonesia is located between 3°54′40″ and 4°5′05″ southern latitude and 122°26′33″ and 122°26′33″ and 122°39′14″ eastern longitude (Figure 1). Kendari City is categorized as tropical climate, in general the maximum temperature is 35 ºC and the minimum temperature is 21 ºC, with air humidity averaging 85.3%. Like the regions in Indonesia, the study area only has 2 seasons, including the dry season and the rainy season.
2.2. Data description and pre-processing

Data that has been collected from Landsat data is obtained from two different sensors (Landsat-7 ETM+ and Landsat-8 OLI), by ordering through the https://espa.cr.usgs.gov page to get the surface reflectance value (sr) in each data included for Bands 1-7 and NDVI data, while thermal bands in band 6 (Landsat-7) and bands 10-11 (Landsat-8) are obtained with data that has been converted to the top atmosphere brightness temperature values and expressed in Kelvin unit. The next process, for optic bands that have a surface reflectance value and thermal bands are then multiplied by a scale factor of 0.0001 and 0.1, respectively [14]. The whole study area belongs to path 112 and row 63 and all images were georeferenced to the WGS-84 datum and Universal Transverse Mercator zone 51S coordinate system to make a stable spatial analysis environment. Comprehensive information relevant to two sensors were summarized to Table 1.

| Sensor                  | Sensor ID               | Acquisition Date      |
|-------------------------|-------------------------|-----------------------|
| Landsat 7 ETM+          | LE71120632001126SGS00   | May 6, 2001           |
| Landsat 8 OLI/TIRS      | LC81120632014282LGN01   | October 9, 2014       |
| Landsat 8 OLI/TIRS      | LC81120632019088LGN00   | March 29, 2019        |

Image processing techniques use ArcGIS 10.6.1 software to find out the UHI intensity in the city of Kendari. The methodology described in the following sections and the conceptual flowchart illustrating the methodology is shown (Figure 2).
2.3. Land cover mapping

The mapping of LC the study area using composite bands 5,4,3 (Landsat-7), and 6,5,4 (Landsat-8) which have a spatial resolution of 30 m. The supervised classifications technique of optical bands for multi-temporal images have been performed using the maximum likelihood algorithm. Class classification is based on actual LC conditions in the field and is limited according to classification requirements. Classification accuracy assessment were done with field knowledge, visual interpretation and also referring the SAS Planet imagery. The accuracy test was calculated through overall accuracy, producer accuracy, and user accuracy based on the error matrix technique and LC map accuracy tests are only conducted for 2019. Five LC classes extracted; (1) trees; (2) mixed vegetation, (3) built-up area, (4) bare soil, and (5) water body, Figure 3. Description information about LC class is listed in Table 2.

Table 2. LC description of study area

| LC class        | Description                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| Tree            | Trees with high density (matured trees, wide canopy trees) [15]              |
| Mixed vegetation| Combination of vegetation types; tree (>3 m), shrub (50 cm – 3 m) and ground cover (<50 cm) [3], [16] |
| Built-up        | Residential area, road body, commercial area, office area                   |
| Bare soil       | Barren land, open land                                                      |
| Water body      | River, pond                                                                 |
2.4. Estimating changes in the Normalized Difference Vegetation Index (NDVI)

The NDVI method is often used in assisting various urban climate modification studies or monitoring climate change due to the expansion of urban, and become one of the main indicators for understanding urban climate [17, 18]. NDVI was derived for all three images using equation (1) [19].

\[ NDVI = \frac{(\rho_{\text{nir}} - \rho_{\text{red}})}{(\rho_{\text{nir}} + \rho_{\text{red}})} \]  

where NIR and Red are the spectral reflectance in the OLI near-infrared = band 5, red = band 4, and ETM+ near-infrared = band 4, red = band 3. This NDVI equation produces values in the range from -1 to 1 [4], [6], [20], where large positive values denote vegetation, small positive values denote built-up or bare soils, and negative to adjacent to negative values denote water bodies [18].

2.5. Estimation land surfaces emissivity from the NDVI

The surface emissivity based on NDVI thresholds [21] is used to retrieve the final LST [22]. Land surface emissivity (\( \varepsilon \)) is calculated using the following equation (2) [18], [20], [21], [23].

\[ \varepsilon = mP_v + n \]  

where \( m = (\varepsilon_v - \varepsilon_s) - (1 - \varepsilon)F \varepsilon_v \) and \( n = \varepsilon_s + (1 - \varepsilon)F \varepsilon_v \), where \( \varepsilon_s \) and \( \varepsilon_v \) are the soil emissivity and vegetation emissivity, respectively. \( F \) is a shape factor whose mean value, assuming different geometrical distributions, is 0.55 [21]. In this study, we used the results [21] for \( m \) (0.004) and \( n \) (0.986). \( P_v \) is the vegetation proportion and was derived using equation (3) [4], [6], [21], [23], [24].

\[ P_v = \frac{(NDVI - NDVI_{\text{min}})}{(NDVI_{\text{max}} - NDVI_{\text{min}})} \]  

where NDVI calculated by equation (1), the \( NDVI_{\text{min}} \) is minimum value of the NDVI, and the \( NDVI_{\text{max}} \) is maximum value of the NDVI.

2.6. LST retrieval

In this study, to produce land surface temperature maps for study area, we used Band 6 (Landsat-7) and Band 10 (Landsat-8), which contained the top of atmosphere brightness temperature values expressed in Kelvin (see section 2.2). The emissivity-corrected LST was calculated as follows (Equation (4)) [25].

\[ LST = T_b/1 + (\lambda \times T_a / \rho) \ln \varepsilon \]  

where \( T_b \) is the at-satellite brightness temperature in degrees Kelvin; \( \lambda \) is the central band wavelength of emitted radiance (11.5 \( \mu \)m for Band 6 [25] and 10.8 \( \mu \)m for Band 10 [23]); \( \rho \) is \( h \times c/\sigma \) (1.438 \( \times 10^{-2} \) m K) with \( \sigma \) is the Boltzmann constant (1.38 \( \times 10^{-23} \) J/K), \( h \) is Planck’s constant (6.626 \( \times 10^{-34} \) J s), and \( c \) is the velocity of light (2.998 \( \times 10^8 \) m/s); and \( \varepsilon \) is the land surface emissivity. Furthermore, the LST value obtained in kelvin units in each image is converted to celcius.

2.7. Mapping UHI

Technically, UHI detection can be done by LST computation (Equation 4.) that utilizes thermal bands on satellite imagery, which the output is a distribution map/distribution of surface temperature [4]. Through LST image classification, UHI can be identified in the following ways (Equation 5-6) [26].

\[ LST > \mu + 0.5 \times \sigma \text{, referred to UHI area} \]  \hspace{1cm} (5)
\[ 0 < LST \leq \mu + 0.5 \times \sigma \text{ denoted non-UHI or rural area} \]  \hspace{1cm} (6)

where \( \mu \) and \( \sigma \) are the mean and standard deviation of temperatures in study area, respectively. Subsequently, the intensity of UHI was defined as the difference between average temperature of UHI area and that of rural area (non-UHI) [6], [12], [26], [24].
3. Result and Discussion

3.1. Land cover changes in Kendari city

The LC map of study area developed using supervised classification method is presented in Figure 3. The accuracy value in 2019 LC map is 92.85%, and from this value it is explained that the LC data in the study area has high accuracy, and can be analyzed and detected changes. Classification accuracy assessment report is given in Table 3.

Table 3. Classification accuracy assessment report for the year 2019

| LC          | Tree | Mixed vegetation | Built-up | Bare soil | Water body | Total     |
|-------------|------|------------------|----------|-----------|------------|-----------|
| Tree        | 1634 | 3                | 0        | 0         | 0          | 0         |
| Mixed vegetation | 103  | 60               | 8        | 0         | 0          | 0         |
| Built-up    | 11   | 2                | 503      | 5         | 6          |           |
| Bare soil   | 12   | 2                | 19       | 11        | 0          |           |
| Water body  | 0    | 0                | 0        | 12        | 0          |           |
| Total       | 1760 | 67               | 530      | 16        | 18         | 2220      |
|             |      |                  |          |           |            | 2391      |
|             |      |                  |          |           |            | 92.85%    |

City of Kendari with a total area of 271.76 km² has accelerated urbanization during the period 2001 to 2019, based on the analysis of Landsat ETM+/OLI that there was a change in the built-up area of 2.71% in the period 2001-2014, and in 2019 image recording the built-up area has increased by 3.44% since 2014 (Table 4), based on this figure in the period 2014-2019 has a more dramatic increase compared to the period 2001-2014. In this case, in the year 2019 the built-up area reached 21.22% of the total area (Figure 3).

The proportion of tree vegetation and mixed vegetation area is quite wide in the study area, with the percentage of tree vegetation and (mixed vegetation) in 2001, 2014 and 2019 amounting to 23% (53.25%), 26.61% (40.11%) and 21.71% (44.96%), respectively from the total area. While bare soil fluctuated in 2001, 2014 and 2019 by 7.79%, 14.54% and 12%, respectively. LC changes in the period 2001-2014 were quite significant in mixed vegetation, which decreased by 13.14%, and increased in the next period of 2014-2019 by 4.85%, while in this period for tree vegetation, bare soil and water body decreased by 4.9%, 2.54%, and 0.85%, respectively (Table 4).

Table 4. Percentage of LC areas and related changes calculated from the classified Landsat ETM+/OLI multi-temporal images

| LC            | 2001 (%) | 2014 (%) | 2019 (%) | Changes area (%) |
|---------------|----------|----------|----------|------------------|
|               |          |          |          | 2001 - 2014      | 2014 - 2019 |
| Tree          | 23.00    | 26.61    | 21.71    | 3.61             | -4.9       |
| Mixed vegetation | 53.25 | 40.11    | 44.96    | -13.14           | 4.85       |
| Built-up      | 15.07    | 17.78    | 21.22    | 2.71             | 3.44       |
| Bare soil     | 7.79     | 14.54    | 12.00    | 6.75             | -2.54      |
| Water body    | 0.89     | 0.96     | 0.11     | 0.07             | -0.85      |
3.2. Changes in NDVI

The NDVI map shows that in some locations there is a scarcity and low quantity of vegetation, especially in built-up areas (such as around road bodies, settlements and port areas) and bare soil. NDVI in these areas in 2001 had a value range of -0.61 - 0.49, in 2014 has a value range of -0.63 - 0.45, and in 2019 has a value range of -0.62 - 0.48 (Figure 4). The minimum NDVI value reflects the low biomass of vegetation cover compared to the built-up increased in the study area. The mean NDVI for areas of study are 0.38, 0.64, and 0.74 for 2001, 2014, and 2019, respectively (Table 5). Vegetation cover plays an important role in minimizing environmental issues in urban cores. Conversely, removal of the vegetation cover leads to environmental criticality in urban sprawls whilst acting as a major contributor for the formation of UHIs [4].

| Year | Min NDVI | Max NDVI | Mean NDVI | Std dev. |
|------|----------|----------|-----------|----------|
| 2001 | -0.61    | 1        | 0.77      | 0.16     |
Table 6. LST statistics on various land cover

| Year | LST Value | Land Cover |
|------|-----------|------------|
| 2001 | 27.79°C   | Built-up   |
| 2014 | 35.29°C   | Built-up   |
| 2019 | 24.96°C   | Built-up   |
|      | 25.45°C   | Tree Vegetation |
|      | 29.22°C   | Tree Vegetation |
|      | 22.53°C   | Tree Vegetation |

3.3. LST from various land cover

The results of satellite image processing in 2001, 2014 and 2019, obtained the spatial distribution of LST on each land cover that can be seen in Figure 5. In Table 6, the highest average LST is found in the built-up area with values of 27.79 °C (in 2001), 35.29 °C (in 2014), and 24.96 °C (in 2019), while the lowest LST is found in the tree vegetation area with values of 25.45 °C (in 2001), 29.22 °C (in 2014), and 22.53 °C (in 2019). LST statistics on various land covers provide information that the highest to lowest LST values in sequence include: built-up area, bare soil, water body, mixed vegetation and tree vegetation. Based on this, the typical pattern of LST is related to the thermal characteristics of the land cover class [27]. The type of tree vegetation shows a much lower LST, because dense trees can reduce the amount of heat stored in the soil and surface structure through transpiration [25].
Figure 5. LST maps derived from multi-temporal Landsat images

Table 6. LST statistics on various land cover

| LC              | 2001    | 2014    | 2019    |
|-----------------|---------|---------|---------|
|                 | Mean    | Std. Dev| Mean    | Std. Dev| Mean    | Std. Dev|
| Tree            | 25.45   | 0.51    | 29.22   | 1.01    | 22.53   | 0.43    |
| Mixed Vegetation| 26.22   | 0.59    | 31.30   | 1.59    | 23.15   | 0.69    |
| Built-up        | 27.79   | 1.91    | 35.29   | 2.00    | 24.96   | 1.44    |
| Bare Soil       | 27.17   | 0.56    | 33.51   | 1.49    | 23.96   | 1.03    |
| Water Body      | 26.34   | 1.08    | 31.63   | 1.59    | 23.56   | 0.66    |

3.4. Mapping of UHI

The average multi-temporal LST on various types of land cover overlaid in the same year is obtained in 2001 at 26.52 °C, in 2014 at 31.75 °C, and in 2019 at 23.47 °C (Table 7). Based the average LST values
that indicate the UHI area in the study area are classified through equations (5) and (6), where the UHI area in 2001 was above 27.11 °C, in 2014 above the temperature of 33.06 °C, and in 2019 above temperature 24.10 °C whose distribution is mapped in Figure 6.

The results of multi-temporal image processing obtained a percentage of the area of UHI in 2001, 2014, and 2019 amounting to 17.76%, 29.23% and 23.09%, respectively (Table 8), in the period 2001 – 2014 the area of UHI has increased, but declined in the 2014 – 2019 period. Based on the image analysis that there is an increase in UHI area in 2014 due to a large reduction in the area of mixed vegetation covering an area of 13.14%, as well as a built-up increase of 2.71% and bare soil at 6.75% of total area (Table 4), in 2014 it might be caused by heat waves which usually last for several days and are quite common during the summer [24]. As through the LC analysis, Kendari City which is dominated by mixed vegetation in its urban areas, reached 44.96% in 2019, this element was the dominant factor affecting the decline temperature in the micro-climate of Kendari City, although in that year there was a decrease in the area of tree vegetation by 4.9%.

**Table 7. LST mean temperatures based on Landsat ETM+/OLI images**

| Year | Min Temp (°C) | Max Temp (°C) | Mean Temp (°C) | St. dev. (°C) | µ + 0.5 * std (°C) |
|------|--------------|---------------|---------------|--------------|-------------------|
| 2001 | 20.01        | 35.74         | 26.52         | 1.18         | 27.11             |
| 2014 | 26.72        | 52.29         | 31.75         | 2.61         | 33.06             |
| 2019 | 19.05        | 29.27         | 23.47         | 1.25         | 24.10             |

**Table 8. Percentage of UHI area during 2001-2019**

| Year | % Non-UHI area | % UHI area |
|------|----------------|------------|
| 2001 | 82.24          | 17.76      |
| 2014 | 70.77          | 29.23      |
| 2019 | 76.91          | 23.09      |
Figure 6. Distribution map of UHI during 2001-2019

3.5. Detection of UHI intensity of 2001-2019 period
The UHI intensity of the study area was obtained through differences in the average LST between areas detected by UHI and the non-UHI or rural area. Table 9 shows that despite the continuous increase in built-up area, the intensity of UHI did not always increase in the observation years, where the UHI intensity in 2001, 2014 and 2019 included: 2.31 °C, 4.75 °C and 2.48 °C, respectively, in the 3 years of observation UHI intensity increased by 2.44 °C in 2014 and then decreased by 2.27 °C in 2019. This can be linked through the LC analysis of mixed vegetation, the urbanization process had an impact on the decrease in the average NDVI in 2014 of 0.64 (Table 5) which is most likely due to the reduction of mixed vegetation areas and the increase in bare soil area due to new land clearing, then the NDVI average increased by 0.74 in 2019, this fluctuation is also possible due to the succession process in the bare soil area.

UHI intensity fluctuations recorded in multi-temporal imagery are not only due to changes in LC and associated evapotranspiration rates, but also caused by anthropogenic heat released from other sources such as vehicles, air conditioners, lighting, and other heat sources [2], which are very closely related to the total population of the region, as is known the highest population density is in the Districts of Kadia, Districts of Wua-Wua and Districts of West Kendari [13]. Other factors that influence these fluctuations
are weather conditions and climate change [24], where the image acquisition on March 29, 2019 was in the middle of the rainy season, so the temperature obtained was relatively lower compared to other image acquisition in 2001 and 2014 which is in the dry season. Referring to the results of the study, there are several areas of Kendari City that are significantly affected by this UHI phenomenon, including: port areas, commercial areas, several public road spots, and densely populated residential areas (Figure 7). Therefore, an urban greening strategy is highly recommended for those areas affected by UHI.

**Table 9.** Intensity of UHI of study area for multi-temporal images data

|                  | 2001 | 2014 | 2019 | Change (°C) |
|------------------|------|------|------|-------------|
|                  |      |      |      | 2001-2014 | 2014-2019 |
| Intensity of UHI (°C) | 2.31 | 4.75 | 2.48 | 2.44 | -2.27 |

**Figure 7.** Several urban features in Kendari City affected by UHI; (a) Main road lacking green areas. (b) The condition of buildings around the port area. (c) One of the commercial areas that lack vegetation. (d) Residential area with less vegetation

4. **Conclusion**

Based on the recording of images from 2001 to 2019, the percentage of built area of Kendari City has now reached 21.22% of the total area, which is likely to experience continuous increase as a result of urban effects, and in this study the authors recommend adding vegetation biomass throughout the administrative area of Kendari City, but the priority scale remains in areas that are significantly affected by UHI, such as port areas, commercial areas, several public road spots, and densely populated residential areas. In addition, urban planners need to pay attention to the ratio of vegetation cover from existing pavement areas for reducing urban heat stress.
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