Retrieving Spatial Variation of Land Surface Temperature Based on Landsat OLI/TIRS: A Case of Southern part of Jember, Java, Indonesia

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Abstract. The study analysis of the land surface temperature (LST) is crucial to maintain the environmental quality of climatic conditions, particularly in Jember as the forest buffer region in the eastern part of Java, Indonesia. In this paper, the land surface temperature (LST) distributions were investigated using Landsat 8 OLI/TIRS images in about 24,008.67 ha of the southern part of Jember. The land surface emissivity (LSE) is also provided in deriving the land surface temperature (LST) from satellite images. The LSE value in the Earth’s surface is retrieved from NDVI (Normalized Difference Vegetation Index) and fractional vegetation cover (Pv). In this case, the reflectance of NIR (Near Infrared) and red bands of Landsat 8 OLI sensor have been acquired to derive NDVI and Pv distribution. Therefore, the LST can be obtained from the LSE coefficient result and brightness temperature (BT) of Landsat 8 TIRS. The results showed that the LST average in the study area increased significantly from 20 \(^\circ\)C in 2013 to 26 \(^\circ\)C in 2018. This condition was triggered by the decreasing area with a high vegetation density about 5% of the study area from 2013 to 2018, which was figured out from the spatial distribution of NDVI and LSE.

1. Introduction
Land surface temperature (LST) is an essential variable in understanding the land surface processes and environmental phenomenon in the Earth [1,2]. Its variability becomes the main parameter to develop methodologies in many environmental studies, including climate change phenomenon, vegetation phenology, urban heat island, ecological environment, and many others. Therefore, the LST pattern should be investigated on both regional or global scales [3,4], particularly in Jember as the region of the forest buffer in East Java, Indonesia.

Identification of land surface temperature (LST) over a large area can be derived effectively through remote sensing technology [5]. Satellite-borne remote sensing data can be used to derive the LST in temporal and spatial variations [6, 7]. Various remote sensing data with different platforms and sensors have been applied to extract or monitor the LST over the Earth’s surface, such as NOAA-AVHRR [8,9,10], MODIS [11, 12, 13], Landsat-5 TM [14,15], Landsat-7 ETM+ [16], Landsat-8 OLI/TIRS [17,18].
Recently, Landsat-8 is the latest satellite of the Landsat mission, was launched on 11 February 2013, which can establish the LST through its sensor data [19]. Land surface temperature (LST) has been acquired from the brightness temperature of the Landsat-8 thermal band by [20]. In this study, we also provided the land surface emissivity (LSE) of Landsat-8 OLI/TIRS for establishing the LST in about 24,008.67 ha of the southern part of Jember. The land surface emissivity (LSE) is an essential parameter in deriving the LST from remote sensing data [21]. Hence, The Normalized Difference Vegetation Index (NDVI) and fractional vegetation cover (Pv) are adopted in this paper due to its sensitivity for obtaining the LSE [22].

The purpose of this study is to retrieve the spatial variation of land surface temperature (LST) in the forest buffer area of the southern part of Jember using Landsat-8 OLI/TIRS. Besides, the spatial distribution of land surface emissivity (LSE) and NDVI were acquired to understand the change-over land surface temperature (LST) between 2013 and 2018 in the study area.

2. Study Area
Jember is situated in the eastern part of Java, Indonesia. Geographically, Jember is located between 7°59’6’’- 8°33’56” and 6°27’29’’-7°14’35” E. This regency surrounded by Probolinggo and Bondowoso regencies in the North, Banyuwangi in the Eastern border, while the Indian Ocean lies in the South, and Lumajang in the West. Land utilization in Jember recency is dominated by forests, about 121,039.61 ha of 329,333.94 ha. Almost 9% of forested areas of East Java expense in Jember widely [23]. Consequently, Jember is a regency as forest buffer region in the Eastern part of Java. The land surface temperature (LST) investigation would be necessary to understand its variation in the research area. As the study area, the southern part of Jember was chosen (see Figure 1).

![Figure 1. The study area](image-url)
3. Methodology
In this study analysis, the land surface temperature (LST) distributions were investigated using dry season Landsat-8 OLI/TIRS images of 2013 and 2018 which have the minimum percentage of land cloud cover over the study area. In the most region, dry season in Indonesia spans from April-September. Therefore, we used Landsat-8 images of July 2013 and April 2018. Band 4 (red) and Band 5 (Near Infrared/NIR) as multispectral bands of OLI sensor, also Band 10 (TIR-1) as a thermal band of TIRS sensor were used for devoting the LST in the study area. Band 11 (TIR-2) of TIRS sensor was not used in this research due to its more enormous calibration uncertainty [24]. Spectral bands specification of Landsat-8 OLI/TIRS is presented in Table 1.

Table 1. Landsat-8 OLI/TIRS bands specification

| Bands  | Band Type       | Bandwidth (µm) | Resolution (m) |
|--------|-----------------|----------------|----------------|
| Band 1 | Coastal/Aerosol | 0.435-0.451    | 30             |
| Band 2 | Blue            | 0.452-0.512    | 30             |
| Band 3 | Green           | 0.533-0.590    | 30             |
| Band 4 | Red             | 0.636-0.673    | 30             |
| Band 5 | NIR             | 0.851-0.879    | 30             |
| Band 6 | SWIR 1          | 1.566-1.651    | 30             |
| Band 7 | SWIR 2          | 2.107-2.294    | 30             |
| Band 8 | Pan             | 0.503-0.676    | 15             |
| Band 9 | Cirrus          | 1.363-1.384    | 30             |
| Band 10| TIR-1           | 10.60-11.19    | 100            |
| Band 11| TIR-2           | 11.50-12.50    | 100            |

3.1. Retrieval Top of Atmosphere (TOA) Spectral Radiance
Top of Atmosphere spectral radiance (Lλ) can be acquired from Landsat data by following the equation below [24].

\[ L_\lambda = M_L * Q_{cal} + A_L \]  

(1)

where \( M_L \) is radiance multiplicative scaling factor for the band-specific, \( Q_{cal} \) is the band specific of L1 (Landsat product), and \( A_L \) is radiance additive scaling factor for the band specific.

In this research, Landsat-8 TIRS band 10 data were converted to TOA spectral radiance. \( M_L \) and \( A_L \) value of Band 10 Landsat-8 TIRS are presented in Table 2.

Table 2. Rescaling factor of radiance from Landsat-8 metadata file

| Rescaling factor | Band 10 |
|------------------|---------|
| \( M_L \)        | 0.0003342 |
| \( A_L \)        | 0.1     |

Besides, the atmospheric correction has been applied through the equation developed by Coll et al. [25]. Several atmospheric parameters provided by Barsi et al. [26] were applied to the formula.

3.2 Conversion of Radiance to Brightness Temperature
Brightness temperature (\( T_b \)) is the temperature that a blackbody which is used to produce the radiance perceived by the sensor [27]. TIRS band 10 of Landsat-8 images can be converted from spectral radiance to brightness temperature using the thermal conversion constant provided in the metadata file. The equation for atmospherically corrected data to convert radiance to brightness temperature is as follows [28]:

\[ T_b = \frac{\kappa_2}{\ln\left(\frac{K_{\lambda\nu} + 1}{\lambda_{AC}}\right)} \]  

(2)
where $T_b$ is top of atmosphere brightness temperature in degrees K, $K_1$ and $K_2$ are the band specific thermal conversion constants from the metadata file (Table 3), $L_{at}$ is the atmospherically corrected cell value as radiance spectra.

### Table 3. Thermal constant from Landsat-8 metadata file

| Rescaling factor | Band 10 |
|------------------|---------|
| $K_1$            | 0.0003342 |
| $K_2$            | 0.1     |

The $T_b$ values can be converted to the Celsius degree by subtracting the result with 273.15 so that the value of brightness temperature ($T_b$) would be changed from Kelvin to Celsius [29].

#### 3.3 Identification of Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) is a vegetation tool commonly used to understand the vegetation condition based on spectral variability of satellite data [30]. Band 4 (red) and band 5 (NIR) on most satellite line-scanning sensor (MODIS, Landsat, and many others) were used to calculate the NDVI [31]. In the calculation of NDVI, both red and NIR channels in DN value have been converted to the reflectance by the following formula [24].

$$
\rho_\lambda' = M_\rho \times Q_{cal} + A_\rho
$$  

where $\rho_\lambda'$ represents TOA planetary spectral reflectance (without correction for solar angle), $M_\rho$ is reflectance multiplicative scaling factor for the band-specific, $Q_{cal}$ is reflectance additive scaling factor for the band-specific, and $A_\rho$ is level 1 pixel value in DN. $M_\rho$ and $A_\rho$ coefficient are shown in Table 4.

### Table 4. Rescaling factor of reflectance from Landsat-8 metadata file

| Rescaling factor | Band 10 |
|------------------|---------|
| $M_\rho$         | 0.0003342 |
| $A_\rho$         | 0.1     |

Thus, $\rho_\lambda'$ does not implicate a correction for the solar elevation angle in the value. Therefore $\rho_\lambda'$ is not actual TOA reflectance. The value of solar elevation angle can be found in the metadata file. By considering a solar elevation angle, the conversion to actual TOA reflectance is shown below [24]:

$$
\rho_\lambda = \frac{\rho_\lambda'}{\cos \theta_{SZ}} = \frac{\rho_\lambda'}{\sin \theta_{SE}}
$$  

where $\rho_\lambda$ is TOA planetary reflectance, $\theta_{SE}$ is local sun elevation angle (provided in the metadata), $\theta_{SZ}$ is local solar zenith angle ($\theta_{SZ} = 90^\circ - \theta_{SE}$).

Then, the reflectance of band 4 (red) and band 5 (NIR) were calculated using the following equation to obtain the NDVI variations in the research study [32].

$$
NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}
$$  

where $\rho_{NIR}$ is the reflectance band in the NIR channel and $\rho_{RED}$ is reflectance band in the red channel.
3.4 Calculation the proportion of vegetation
The proportion of vegetation (Pv) on the Earth’s surface was calculated by considering the variability of NDVI in a particular area. The Pv was calculated using the following equation by Sobrino and Raissouni [33]. This equation is derived, according to Carlson and Ripley [34].

\[ P_v = \left( \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \right)^2 \] (6)

where \( NDVI_v \) and \( NDVI_s \) are the NDVI values for bare soil and full vegetation respectively (\( NDVI_v = 0.5 \) and \( NDVI_s = 0.2 \)).

3.5 Derivation of Land Surface Emissivity
Land surface emissivity (LSE(\( \varepsilon \))) is an essential parameter to estimate land surface temperature (\( T_s \)) in perceiving the global-change studies related to our environment [35]. According to Sobrino et al. [36], Skokovic et al. [37] have been developed an equation to calculate \( \varepsilon \) from the proportion of vegetation as shown below.

\[ \varepsilon = \begin{cases} 
  a + b \rho_{\text{red}} & \text{NDVI} < NDVI_v \\
  \varepsilon_s (1 - P_v) + \varepsilon_v P_v & NDVI_s \leq NDVI \leq NDVI_v \\
  0.99 & NDVI > NDVI_v 
\end{cases} \] (7)

where \( a \) is a coefficient of 0.979, \( b \) is a coefficient of 0.046, \( \rho_{\text{red}} \) is the reflectance of band 4 (red), \( \varepsilon_s \) is soil emissivity value (0.971), and \( \varepsilon_v \) is vegetation emissivity value (0.987). The concept to obtain the \( \varepsilon \) variability by considering the NDVI variations in the different land surface has applied as follows [38]:

(a) NDVI<0.2 (NDVI< NDVI_s) represents the bare soil, and the emissivity is obtained from the reflectivity in the red channel (\( \rho_{\text{red}} \))
(b) NDVI>0.5 (NDVI>NDVI_v) represents the fully vegetated area of the land surface, and a constant emissivity of 0.99 has been assumed.
(c) NDVI >0.2 to <0.5 represents a mixture area of bare soil and vegetation, and the emissivity is calculated based on the proportion of vegetation (Eq. 6) and applied it to the Eq. (7) of \( \varepsilon_s (1 - P_v) + \varepsilon_v P_v \).

3.6 Retrieval the and surface temperature
In this study, the dynamic of land surface temperature (LST) was retrieved through the equation developed by Stathopoulou and Cartalis [39] as follows.

\[ T_s = \frac{T_b}{1 + \left( \frac{\lambda}{\rho} \ln \varepsilon \right)} \] (8)

where \( T_s \) is the land surface temperature (LST) in °C, \( T_b \) is brightness temperature which already converted to °C, \( \lambda \) is the wavelength of emitted radiance from Landsat-8 TIRS band 10 (10.8 \( \mu m \)), \( \rho \) is \( h \times c/\sigma \) = 1.4388 \( \times 10^{-2} \) m K = 14388 \( \mu K \) (\( h \) is Planck’s constant of 6.626 \( \times 10^{-34} \) J s, \( c \) is the velocity of light of 2.998 \( \times 10^{8} \) m/s, \( \sigma \) is the Boltzmann constant of 1.38 \( \times 10^{-23} \) J/K), and \( \varepsilon \) is the surface emissivity.
4. Result and Discussion

Time sequence of 2013 and 2018 Landsat-8 OLI/TIRS were utilized in this research to monitor the land surface temperature distribution in the southern part of Jember, which take apart as the forest buffer region. The NDVI variations were employed to identify the vegetation condition in 2013 and 2018. NDVI is a vegetation tool for application in environmental monitoring, which can Figure vegetation condition effectively [40]. The variations of NDVI describing the spatial distribution of vegetation condition in 2013 and 2018 within the research area are shown in Figure 2.

Figure 2 shows that spatial distributions of NDVI in the research area tend to decrease from 2013 to 2018. Vegetation monitoring using NDVI has become an essential parameter to evaluate the vegetation density in a particular area, while dense vegetation has a high NDVI [41]. According to Figure 2, the vegetation density based on NDVI in the study area was calculated and presented in Table 5.

Table 5. Type of vegetation density based on NDVI values

| Class | NDVI | Dense of vegetation | Area (ha) | Percentage (%) |
|-------|------|----------------------|-----------|-----------------|
|       |      |                      | 2013      | 2018            | 2013 | 2018 |
| 1     | <0.2 | less                 | 168.39    | 297.45          | 0.70 | 1.24 |
| 2     | 0.2-0.5 | moderate          | 8,836.02  | 10,022.04       | 36.80 | 41.74 |
| 3     | >0.5 | high                | 15,004.26 | 13,689.18       | 62.50 | 57.02 |
| Total |      |                      | 24,008.67 | 24,008.67       | 100.00 | 100.00 |

Based on Table 5, it shows that the area with high vegetation density decreased from 15,004.26 ha in 2013 to 13,689.18 ha in 2018, while the percentage of the less and moderate class of vegetation density increased during the observation time. Vegetation monitoring using only the NDVI as the parameter was not enough to evaluate the dynamic of land surface temperature in the study area. Hence, we also developed the land surface emissivity ($\varepsilon$) to explain the detailed condition of the land surface in the research area.

![Figure 2. Spatial variations of NDVI in the research area](image-url)
The land surface emissivity (LSE) variations in 2013 and 2018 throughout the region are presented in Figure 3 spatially.

Figure 3 indicates that the land surface of full vegetated represents the green colour in the map decreased from 2013 to 2018. The land surface classes based on the spatial distribution of LSE (ε) are presented in Table 6 as follows.

| Class | Land surface classes | LSE         | Area (ha) | Percentage (%) |
|-------|----------------------|-------------|-----------|----------------|
|       |                      | 2013  | 2018  | 2013 | 2018 |
| 1     | bare soil            | <0.971 | 5.49  | 10.98 | 0.02 | 0.05 |
| 2     | mixture of soil and vegetation | 0.971-0.987 | 8,990.46 | 10,225.35 | 37.45 | 42.59 |
| 3     | fully vegetated      | >0.987 (=0.99) | 15,012.72 | 13,772.34 | 62.53 | 57.36 |
|       | Total                |         | 24,008.67 | 24,008.67 | 100.00 | 100.00 |

Table 6 shows that the percentage of fully vegetated area decreased from 62.53 in 2013 to 57.36 in 2018. However, the percentage of bare soil and a mixture of soil and vegetation increased during the five years of the monitoring period. The variations of land surface emissivity (ε) can be used to understand the land surface temperature in the study area because it has a great potential in separating the land surface classes effectively based on its variability.

The land surface temperature (LST) was then developed to all datasets. The spatial distributions of the LST based on Landsat-8 OLI/TIRS in 2013 and 2018 are shown in Figure 4.

Figure 4 visualizes that the land surface temperature changed significantly during the observation time of 2013 to 2018. The area of LST based on its interval was also calculated in Table 7.
Table 7. LST interval of the study area

| LST (in Celcius) | Area (ha) 2013 | Area (ha) 2018 | Percentage (%) 2013 | Percentage (%) 2018 |
|-----------------|---------------|---------------|----------------------|----------------------|
| 16-20           | 19,935.54     | 0.00          | 83.03                | 0.00                 |
| 20-24           | 1,675.44      | 9,478.62      | 6.98                 | 39.48                |
| 24-28           | 1,882.08      | 6,726.96      | 7.84                 | 28.02                |
| 28-32           | 484.02        | 5,227.29      | 2.02                 | 21.77                |
| 32-36           | 31.59         | 2,484.72      | 0.13                 | 10.35                |
| 36-41.13        | 0.00          | 91.08         | 0.00                 | 0.38                 |
| **Total**       | **24,008.67** | **24,008.67** | **100.00**           | **100.00**           |

The results show that the LST interval changed from 16°C-36°C in 2013 to 20°C-41.13°C in 2018. The land surface temperature (LST) in 2013 is dominated by the LST interval of 16°C-20°C in about 83.03%, while in 2018 is dominated by 20°C-24 °C about 39.48%. It means that the temperature degree during the monitoring period has increased in the study area.

Figure 4. Spatial distributions of LST in 2013 and 2018

The average of LST values related to the LSE is presented in Table 8. Based on Table 8 it shows that the LST increased from 20°C in 2013 to 26°C in 2018, while the LSE decreased from 0.986 in 2013 to 0.984 in 2018. The dynamic of this condition was triggered by the decreasing area with high vegetation density about 5% of the study area from 2013 to 2018, which figured out from the variations of NDVI and LSE in Figure 2, Figure 3, Table 5, and Table 6.
Table 8. The average of LST and LSE in 2013 and 2018

| Year | LST (℃) | LSE  |
|------|---------|------|
| 2013 | 26      | 0.984|
| 2018 | 20      | 0.986|

5. Conclusion
This research attempts to retrieve the spatial distribution of the land surface temperature (LST) throughout the southern part of Jember based on Landsat-8 OLI/TIRS of satellite-borne scanning sensor. We found that the vegetation condition over the land surfaces figured by the NDVI and LSE (ε) can trigger the spatial variations of the land surface temperature (LST). Besides, the brightness temperature at the satellite sensor are also crucial in retrieving the land surface temperature (LST) on the Earth’s surface. The results of LST estimation can contribute to monitoring the forested region and the forest fringe area as an early warning system in preserving its ecosystem from the climate change phenomenon.

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