Estimation of land surface temperature in Dieng volcanic complex using tir-based satellite imageries

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Abstract. The satellite-based Land Surface Temperature (LST) and its anomaly values were observed in the geothermal area of Dieng Volcanic Complex (DVC). Landsat-8 and ASTER product on surface kinetic temperature (AST-08) were selected, based on its spectral and spatial resolution characteristics, as well as its retrieval methods applied for the LST extraction. Statistical analysis was performed on the pixel-integrated temperatures to cross-compare both of the remote sensing-based LST. Thermal Infrared (TIR)-based LST was also correlated with the LST reference from a field measurement. Correlation between the field measurement and satellite-based LST was considered insignificantly weak; while correlation between the satellite-based LST (Landsat-8 with SW and ASTER-based with TES) was significantly strong. The LST registration approaches cause difference on correlation strength. Field-based LST directly measured the ground kinetic temperature of sample points with infrared thermometer; while satellite-based LST sensed the thermal radiation emitted by the represented objects in a pixel area that possibly mixed the LST values. The clusters in response to geothermal features reflected bias result; as the thermal anomalies were less pronounced, observed from both of the satellite-based LST estimation.

1. Introduction

Geothermal resource is the heat energy stored within the earth’s interior [1]. The thermal energy has three main heat sources from: (a) radioactive isotopes decay, (2) residual heat of earth’s core from its early formation, and (3) gravitational pressure where the heat rises up with depth [1, 2, 3]. Geothermal reservoir stores the heat energy at different depths. The near-surface geothermal system can extracts the heat from depth of 150 – 400 meters; while the deep system may extract from depth of 400 to thousand meters below [3].

Geothermal system can transport the subsurface heat to the ground surface, discharged as thermal manifestations [3, 4, 5]. The surface thermal signatures may appear as fumaroles, solfatara, hot springs, travertine, heated ground, and mud pools. In many cases, these surface expressions also have distinctive characteristics as rock alterations and sinter deposits [4, 6].

The temperature of ground surface has a function of emitted thermal radiation by the objects [7]. The detection of temperature peaks or hotspots features can be assessed through the Thermal Infrared (TIR) data. In-situ measurement on object temperature can be retrieved by using infrared thermometer [8], while TIR-based remote sensing has been beneficial as the cost-effective approach for detecting temperature anomalies [4, 5, 6, 9].
Surface thermal anomalies related to geothermal activity can be detected through the threshold of significant deviation from the average temperatures [3, 10]. The detectable signatures from geothermal heating give consistent peak temperatures at the same location over time. While the questionable hotspots, in regards to false anomalies, can be detected as thermal signs occurred at a single time. False thermal anomalies can be caused by the presence of vegetation covers, topographic effects, hotspots (volcano eruption, forest fires), material compositions, and solar heating [4, 6, 11].

The general aims of this work are to retrieve the satellite-based Land Surface Temperature (LST) and observe its anomaly values, associated with the geothermal features; provided by some alternatively different platforms and methods. Landsat-8 and ASTER product on surface kinetic temperature (AST-08) were selected based on its spectral and spatial resolution characteristics, as well as its retrieval algorithm applied. Statistical analysis was performed on the pixel-integrated temperatures to cross-compare both of the remote sensing-based LST, and also with the LST field measurement collected from a research by Napitupulu, 2017.

![Figure 1. ALOS PALSAR-based Topography of the DVC area. Blue, red, and purple rectangles indicate the DVC, Dieng concession area, and Candradimuka prospect area, respectively. Black triangles and red dots show the spatial distribution of mountains and thermal manifestations](image)

Source: (BIG, 2006; Geo Dipa Energi, 2017b; JAXA/METI, 2010; Layman et al., 2002; MEMR, 2017; Pambudi et al., 2015; van Bergen et al., 2000; Zen, 1971), Data Processing, 2018

2. Study Location
Dieng Geothermal field is situated on a broad highland in the Province of Central Java, known as Dieng Volcanic Complex (DVC) (see Figure 1). The DVC is characterized by a caldera structure with volcanic edifices, hosted in a Quaternary volcanic range. The area has an extent of ± 84 km², and reaches the elevation of ± 2.565 meter above the sea level [12, 13].

The DVC consists of two geothermal sectors i.e., Dieng working field and Candradimuka prospect area. Both are located on the eastern and western part of the DVC, respectively [14]. The total potency
of Dieng field reaches up to 400 Mega-Watt (MW). The first unit has an installed capacity of 60 MW, that generates electricity for the islands of Java, Madura, and Bali. It has further development plans for the second, third, and fourth power plants on 55 MW each [15].

Dieng geothermal field has potential shallow heat source, hypothetically located at depth of 5 – 10 km [16]. The surficial thermal features associated with hydrothermal activity in the DVC consist of: fumaroles and solfataras, steaming ground, acid sulphate and sulphate-bicarbonate springs, gas emission vents, and mud pool [12]. Figure 1 illustrates the distribution of the thermal manifestation on the DVC area, shown as the red dots.

3. Thermal Infrared (TIR)-based Land Surface Temperature (LST) Estimation

Thermal Infrared (TIR) spectrum is directly related to sense thermal radiation emitted by the object [17]. Although having limitation on the ground penetration capacity compared to microwave domain, TIR sensor provides a higher spatial resolution [18]. Several important elements related to the thermal sensing are: radiance-kinetic temperatures, emissivity, and thermal inertia [19].

Kinetic temperature measures the thermal energy constituting a body, through a direct contact (internal thermal manifestation). While radiant temperature measures the emitted energy radiated by the object (external thermal manifestation) [18]. In accordance with radiation, the object ability to radiate thermal energy is referred as emissivity; and the measure of material response to temperature change refers to thermal inertia [17]. Thermal inertia is a function of material density, thermal conductivity, and heat capacity [20].

Land Surface Temperature (LST) is a derivation product from TIR-based remote sensing that relies on the emissivity of materials. The emissivity values depends on element characteristics (e.g. texture, dryness, thermal inertia) [19, 20]. Emissivity can be retrieved from various approaches through: land-cover classification, vegetation index [33], fraction vegetation cover, and spectral ratio [21].

The basic challenges in estimating emissivity and temperature values through remote sensing are governed by: (1) emissivity over the complex surfaces, (2) material properties (thermal inertia, albedo, moistures) [20, 22, 23], (3) atmospheric condition (solar radiation, precipitation, humidity) [3, 8, 24, 25], (4) radiation from mixing objects (pixel heterogeneity) [24, 26], and (5) topographical characteristic (slope, aspect) [5, 19, 22].

The surface thermal anomalies associated with geothermal activity can be detected by looking at the threshold of significant deviation from the average temperatures [3, 27]. Thermal signature and its association with thermally active regions were analysed through the anomaly threshold value and its spatial distribution. The temperature anomalies are statistically detectable through the function of mean and standard deviation (z-values) on certain confidence levels.

4. Methods for Retrieving Satellite-based Land Surface Temperature (LST) Estimation

There are three general approaches to retrieve the TIR-based LST [18, 21, 28, 29, 30, 31, 32]:

4.1. Single-Channel (SC) Algorithm

SC algorithm uses radiance values received from a single TIR band as an input for a Radiative Transfer Equation (RTE) [33, 34, 35]. RTE method uses three parameters of: land-leaving (upward) radiance, down-welling irradiance (downward), and atmospheric transmissivity [31]. The shortcoming of RTE method requires a complex atmospheric profiles computation to process its atmospheric simulation [18].

4.2. Two-Channel (TC) or Split-Window (SW) Algorithm

SW Algorithm expresses linear combination of multiple TIR channels on measuring at-sensor radiances, proportionally to surface emitted radiance [31, 36, 37, 38]. SW method requires the known emissivity in two-adjacent bands on sufficient accuracy [39]. Higher spatial resolution may support SW method better, associated with its emissivity measurement [40].

4.3. Multi-Channels with TES (Temperature-Emissivity Separation) Algorithm
TES is applied for ASTER dataset [24]. It consists of three modules: (1) Normalized Emissivity Method (NEM) to fix single emissivity through land-cover separation, (2) spectrum ratio of obtained NEM emissivity divided by its mean value, and (3) Min-Max Emissivity Differences (MMD) attributed to scaling regression of emissivity contrast [24]. The issue with TES relates to the different treatment on low and high emissivity contrast, that tends to under-estimate the LSE and over-estimate the LST. Another issue is related to the atmospheric condition that may affect the correction procedure [37].

5. Dataset
The dataset for Land Surface Temperature (LST) extraction was based on the satellite-based interpretation and field-based measurement. The processing tools were in ArcGIS and ENVI software. The satellite-based TIR dataset used on this work were Landsat-8 OLI-TIRS and ASTER product on Surface Kinetic Temperature (AST_08);
- Landsat-8 OLI/TIR; acquisition: May 29th, 2015 at 02:47:11 UTC [41]
- ASTER (AST_08); acquisition: May 5th, 2015 at 03:06.00 UTC [42]
AST_08 is a surface temperature product generated by TES (Temperature-Emissivity Separation) algorithm on five thermal channels (8 – 12 µm) [24, 31]. The AST_08-based LST product was developed from the Planck’s Law, using surface emissivity values from AST_05 product. It is to scale the emitted radiance and minimize the effect of reflected down-welling irradiance [28].

The field-based observation on ground kinetic temperature was collected from a fieldwork by Napitupulu (2017). There were 44 temperature measurements around Dieng geothermal field (see Figure 3), by using infrared thermometer. There are 20 samples were from geothermal features of craters and hot waters; and 22 samples were from the non-geothermal features (e.g soil and vegetation). Field sampling was conducted on March 29th, 2017 at 9 AM – 12 PM [43].

6. Methodology
Land Surface Temperature from Landsat-8 was retrieved from Split Window Algorithm (SWA) method for two TIR channels [38]. Landsat processing encompassed: radiometric and atmospheric correction, also Land Surface Emissivity (LSE) estimation based on the Fractional Vegetation Cover (FVC). The FVC is associated with vegetation proportion, within a mixed-pixel of vegetation and non-vegetation features [44, 45]. The base method for LST retrieval is atmospheric correction, to diminish the effects of atmospheric transmittance and downward sky irradiance [18, 31].

6.1. Radiometric Correction
6.1.1. Radiometric calibration.
A conversion from Digital Number (DN) into at-sensor emitted radiances (Top of Atmosphere spectral radiance) for the OLI and TIRS bands [46].

\[ L_\lambda = M_\lambda X Q_{cal} + A_\lambda \]

Where:
- \( L_\lambda \) = ToA radiance (Watts/(m²*srad*µm));
- \( M_\lambda \) = Band-specific multiplicative rescaling factor (Radiance_Mult_Band_x);
- \( Q_{cal} \) = Quantized and calibrated DN values;
- \( A_\lambda \) = Band-specific additive rescaling factor (Radiance_Add_Band_x)

6.1.2. Brightness temperature. Conversion of Top of Atmosphere (ToA) spectral radiance to at-sensor ToA Brightness Temperature

\[ T_B = \frac{k_2}{\ln \left( \frac{k_2}{k_2 + 1} \right)} \]

Where:
- \( T_B \) = ToA Brightness Temperature (K);
L_{\lambda} = \text{ToA radiance (Watts/(m}^2\text{srad*um))};
K_1 \& K_2 = \text{Band-specific thermal conversion constants (K1\_Constant\_Band-1 \& K2\_Constant\_Band-2)}

6.2. Emissivity Extraction

6.2.1. Fractional Vegetation Cover (FVC). The emissivity estimation.

\[
\text{NDVI} = \frac{\text{NIR}(5) - \text{Red}(4)}{\text{NIR}(5) + \text{Red}(4)}
\]

\[
\text{FVC} = \frac{\text{NDVI} - \text{NDVI}_{\text{soil}}}{\text{NDVI}_{\text{vegetation}} - \text{NDVI}_{\text{soil}}}
\]

Where: \text{NDVI} = \text{Vegetation Index}; \text{FVC} = \text{Fractional Vegetation Cover};
\text{NDVI}_{\text{soil}} = \text{Lowest Soil Vegetation Index}; \text{NDVI}_{\text{vegetation}} = \text{Highest Vegetation Index}

6.2.2. Land Surface Emissivity (LSE). Values derived from the FVC [16].

\[
\text{LSE Band}_n = (\text{E}_s \text{ Band}_n \times (1 - \text{FVC})) + (\text{E}_v \text{ Band}_n \times \text{FVC})
\]

\[
M = \frac{\text{LSE Band}_{10} + \text{LSE Band}_{11}}{2}
\]

\[
\Delta M = \text{LSE Band}_{10} - \text{LSE Band}_{11}
\]

Where:
\text{LSE Band}_n = \text{LSE values from band-n};
M = \text{mean LSE};
\Delta M = \text{LSE difference};
\text{E}_s \text{ Band}_n \& \text{E}_v \text{ Band}_n = \text{soil emissivity of band-n and vegetation emissivity band-n};
\text{LSE Band}_{10} \& \text{LSE Band}_{11} = \text{corrected emissivity of band-10 \& band-11}

6.3. LST estimation with SW algorithm [47] [34]

\[
\text{LST} = \text{TB}_{10} + C_1 (\text{TB}_{10} - \text{TB}_{11}) + C_2 (\text{TB}_{10} - \text{TB}_{11})^2 + C_0 + (C_3 + C_4 \text{ W}) (1 - M) + (C_5 + C_6 \text{ W}) \Delta M
\]

Where:
\text{LST} = \text{Land Surface Temperature (K)};
\text{TB}_{10} \& \text{TB}_{11} = \text{Brightness (at-sensor) Temperature (K) of band-10 \& band-11};
C_0 - C_6 = \text{Split Window Coefficients};
\text{W} = \text{Atmospheric Water Vapour Content (g/cm}^2\text{)};
M = \text{mean LSE of TIR bands (b-10 and b-11)};
\Delta M = \text{LSE difference}

The thermal anomaly values were estimated through a statistics observation, by looking at the high deviation from the average temperatures [38, 48]. Spatial analysis observed the pattern significance (clustering or dispersing) of the hot and cold signatures, by analysing the z-values (standard deviation) and p-values (probability) of the dataset. The Getis-Ord Gi* tool provides spatial analysis for clustering the pattern of significance values, at certain confidence levels [49]. To highlight the anomalies associated with geothermal activity, extracted LST was masked-off with the built-up areas, thus eliminating the values affected by non-geothermal features.

7. Results
The Landsat-based LST retrieval was commenced by generating the Fractional Vegetation Cover (FVC) values for emissivity analysis. Figure 2a shows the resultant image of NDVI-based FVC, generated from the V-NIR bands of Landsat-8. In this figure, higher FVCs (darker green) were in association with forestry and shrubs areas, as shown on the land-cover reference from Figure 2b. While lower FVCs (white to light green shades) pronounced the settlement areas and agricultural fields (yellow and pink colour), majorly spread throughout the centre part of study area.

Figure 2. The Fractional Vegetation Cover (Left) and Landcover map (Right) of the DVC
Source: (BIG, 2006; Geo Dipa Energi, 2017b; JAXA/METI, 2010; MEMR, 2017)

7.1. The Land Surface Temperature (LST) Mapping and Its Thermal Anomalies Observation
Figure 3 shows the TIR-based LST extraction images, and Table 1 provides the statistics of estimated temperatures. The extracted values of LST ranged on 14.93 – 39.6 °C (for Landsat-based LST) and 15.62 – 42.65 °C (for Aster-based LST). The mean surface temperatures values were 25.09 °C and 25.95 °C for Landsat-based and Aster-based LST, respectively. The threshold values for temperature anomalies started from 32.03 °C (for Landsat-based LST) and 32.77 °C (for Aster-based LST).

From the spatial relation between the LST values and its land covers (Figure 3 and Figure 2b), the spatial distribution of LST shows that the lower temperatures (green shades) were associated with forestry on steeper relief; while higher temperatures (yellow shades) were widely distributed on the agricultural land (paddy and dry-crop land). The highest surface temperatures (reddish shades) were highlighting the settlements areas, mainly spread out on the centre part of study area.

| Basic Statistics | Min   | Max   | Mean  | StdDev | Threshold* |
|------------------|-------|-------|-------|--------|------------|
| Landsat-8        | 14.93 | 39.60 | 25.09 | 3.47   | 32.03      |
| AST-08           | 15.65 | 42.65 | 25.95 | 3.41   | 32.77      |

*Threshold values = Mean + (2 * Std.Dev)

Source: Data Analysis, 2018
Figure 3. Extracted TIR-based LST from: Landsat-8 (Left) and ASTER AST-08 (Right). Lower to higher LST were indicated in greenish to reddish shades. Source: (BIG, 2006; JAXA/METI, 2010; NASA, 2019; USGS, 2019) and Data Processing, 2018

Figure 4. Detectable thermal anomaly cluster on the DVC using the Getis-Ord Gi* tool; (a1) and (a2) for the LST before built-up masking for Landsat and Aster-based, respectively, (b1) and (b2) for the LST after built-up masking for Landsat and Aster-based, respectively. Source: (BIG, 2006; JAXA/METI, 2010; NASA, 2019; USGS, 2019) and Data Processing, 2018
The thermally high regions can potentially highlight the active pulses associated with geothermal activity. The presence of this thermal signatures were interpolated through the Getis-Ord Gi* tool to cluster the significance of hotspots pattern for confidence levels of 95% (see Figure 4).

To highlight the distinguished anomalies related to geothermal association, extracted LST was masked-off with the built-up areas, thus retaining the high temperatures disassociated from built-up area. Figure 4a depicts the apparent anomaly clusters detected on the DVC area, while Figure 4b displays the anomaly clusters that were already masked-off from the built-up area.

| Table 2. Descriptive Statistics for Land Surface Temperature (°C), Before and After the Built-up Masking |
|---------------------------------------------------------------|
| **Basic Statistics** | **Thermal Anomalies on the DVC** | **Built-up areas masked-off Thermal Anomalies** |
|---------------------|-------------------------------|---------------------------------------------|
|                     | Min                           | Max                           | Mean | StdDev          | Min        | Max       | Mean           | StdDev          |
| Landsat-8           | 32.85                         | 39.85                         | 25.09 | 3.47            | 32.85      | 35.85     | 34.35          | 1.11            |
| AST-08              | 32.85                         | 42.65                         | 25.95 | 3.41            | 32.85      | 41.95     | 36.55          | 2.33            |

Source: Data Analysis, 2018

Table 2 provides the estimated thresholds for temperature anomaly before and after the built-up areas masked-off. After the masking, thermal anomalies ranged for 32.85 – 35.85 °C and 32.85 – 41.95 °C for Landsat-based and Aster-based LST, respectively.

Referring to Figure 4, the anomaly clusters with relatively consistent location were situated around the built-up areas. The anomaly clusters appeared similar for both of the Landsat-based and ASTER-based LST, performed by different methods and acquisition time. The thermally-active region in response to geothermal surface was less pronounced from both of satellite-based LST. This bias result could have influences from the topographical relief, atmospheric effect, and its land coverage. Besides, within 90–100 meter of spatial resolution, the thermal manifestations registered within sub-pixel may get affected by its surrounding temperature. Thus, the proportion of geothermal features compared to the agricultural fields dominance might affect the registered temperatures.

8. **Statistical Correlation Analysis**

The LST extractions were statistically analysed under the significance level (α.05) for: (a) significance (P-value) of correlation coefficient (r) with ANOVA test; (b) determination coefficient (R^2) that reflects data variance and its population representation; (c) accuracy assessment, through Standard Error for satellite-interpreted and field-measured temperature estimation. Table 3 displays the descriptive statistics of correlation analysis between the field-based and satellite-based LST.

| Table 3. Descriptive Statistics Correlation between the Field-based and Satellite-based LST |
|---------------------------------------------------------------|
| **Statistic Elements** | **All Samples** | **Geothermal Features** | **Non-geothermal Object** |
|------------------------|-----------------|-------------------------|---------------------------|
|                        | FL & LL & AL    | FL & LL & AL            | FL & LL & AL              |
| Pearson r              | .030            | .037                    | .775                      |
| R^2                    | .001            | .001                    | .600                      |
| P-value                | .844            | .813                    | .000                      |
| Std. Error             | 21.279          | 21.274                  | 1.309                     |

Where; FL = Field-based LST; LL = Landsat-based LST with SW algorithm; AL = ASTER-based LST with TES algorithm;

\[ df = 42 \text{ (for all samples), } 18 \text{ (for geothermal samples), } 22 \text{ (for non-geothermal samples); } \alpha = .05 \]

Source: Data Analysis, 2018
There were insignificantly weak correlations between the field-based and satellite-based LST (P-values > $\alpha$.050) and low r values), where:

- For Landsat-8 $\rightarrow$ P-values = .844; r = .030 (for all samples); P-values = .127; r = .353 (for geothermal samples); and P-values = .152; r = .301 (for non-geothermal samples)
- For ASTER AST-08 $\rightarrow$ P-values = .813; r = .037 (for all samples); P-values = .370; r = .212 (for geothermal samples); and P-values = .054; r = .398 (for non-geothermal samples)

- There were significantly strong correlations between the Landsat-based and ASTER-based LST (P-values < $\alpha$.05) and r > 0.5), applied for the correlations between all samples.

- Coefficient of determinations ($R^2$) between the field-based and satellite-based LST were considered low, compared to the $R^2$ between the satellite-based LST. It indicated that the LST field samples may not reflect the population, mainly due the temporal acquisition differences, and heterogeneity of pixels that possibly mixed the LST values.

- Standard Error (SE) levels were considered higher between the field-based and satellite-based LST, than on between satellite-based interpretations. Higher levels of SE indicate lower accuracy that could possibly contributed from its extraction approaches; where both of satellite-based LST registered the emitted radiance of sub-pixel object, while the field-based LST directly measured kinetic temperature from the feature point.

9. Conclusion

Satellite-based Land Surface Temperatures (LSTs) were extracted from two different platforms and algorithms of: Landsat-8 with Split Window Algorithm, and ASTER surface kinetic product (AST-08) with TES algorithm. The satellite-based LSTs were correlated with the ground-based LST measurement using infrared temperature, by Napitupulu, 2017. Correlation between the field-based and satellite-based LSTs (Landsat and ASTER) was considered insignificantly weak; while correlation between the satellite-based LSTs (Landsat-8 with SW and ASTER-based with TES) was considered significantly strong.

The coefficient of determination ($R^2$) statistics indicated that the LST field samples may not reflect the population, mainly due the temporal acquisition differences, and heterogeneity of pixels that possibly mixed the LST values. The standard Error (SE) between field-based and satellite-based LST indicated lower accuracy, that could possibly contributed from its extraction approaches. Both of satellite-based LST registered the emitted radiance of sub-pixel object, while the field-based LST directly measured kinetic temperature from the feature point.

The anomaly detection in response to geothermal surface was less pronounced from both of satellite-based LST. This could be biased due to the influences of topographical relief, atmospheric effect, and its land coverage. Moreover, thermal manifestations that were registered within sub-pixel may get affected from its surrounding temperature within a 90–100 meter spatial resolution of the TIR-channels. Thus, the proportion of geothermal features in comparison to the agricultural fields dominance might affect the registered temperature.

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