Identifying Upflow Zone Based on Thermal Infrared (TIR) Sensor and Field Measurements at Volcanic Field

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Abstract. Upflow zone identification at volcanic fields is crucial for geothermal resource exploration. The common problem to identify the upflow zone using conventional mapping method is time-consuming and the limitation of access to the area. The application of satellite imaging as ground-truthing is aimed to increase the effectiveness of upflow zone detection at geothermal fields. This study selected the volcanic field around the Bandung Basin for a model case. The data used in this study were thermal images of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Thermal Infrared Radiometer (TIR) by the night observations. The TIR data were corrected and calibrated by Visible Near Infrared Radiometer (VNIR) to measure Land Surface Temperature (LST). We then focused our analysis around a volcanic area that showed high LST at the Papandayan crater and other manifestations. Validations were carried out by measuring surface temperature and gas concentrations including SO₂ and CO₂. The reading value of the gases was different on each location, but the pattern of the gases was relatively similar especially the SO₂ gas pattern. The SO₂ gas showed a relatively constant trend of gas concentration over time in the upflow zone, but in the outflow zone showed an increase pattern with the time whose reading values were lower than those on the upflow. On the contrary, the non-geothermal features showed that the SO₂ concentration decreased with the time towards almost 0. According to the retrieved LST, the surface manifestations were located not only at the high anomaly but also at medium anomaly depending on the manifestation dimension. The gas and temperature measurements proved that LST could be used to enhance the effectiveness of upflow zone identification.

1. Introduction
Indonesia located within the ring of fire has a high potential in geothermal energy. There are at least five components of a complete geothermal system: heat source, reservoir, caprock, recharge area, and discharge area (Figure 1). The discharge area can be divided into upflow and outflow zones. The upflow
zone is a primary target for large scale power production in a geothermal system because of the high temperature and pressure suitable for power generation [1]. The zones have high temperature and pressure because of their short distance to the heat source [2]. The geothermal manifestations located at the upflow zone can be identified by acidic springs and fumaroles, whereas the outflow zones by hot springs with near neutral pH [1]. The outflow zones serve as a secondary target of geothermal power production due to medium to low temperature and pressure.

The detection of the upflow zone using conventional methods usually was hampered by some problems such as time consuming and limited access to the area. To overcome these problems, this paper proposes a method to enhance the effectiveness of satellite remote sensing to detect upflow zones with field validations and measurements. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Thermal Emission Radiometer (TIR) data can be used to detect Land Surface Temperature (LST) with correction and calibration [3]. The night observation data were used to minimize noise from the environment [4]. LST can be used to locate geothermal surface manifestations [5]. In addition, the combination of satellite imaging and gas measurement was used to classify the upflow and outflow zones correctly in this study. The study area was selected around the Bandung Basin due to unique morphology surrounded by active volcanoes (Figure 2).

Figure 1. Conceptual model of geothermal system related to an active volcanic field typical for a magmatic arc setting above a subduction zone [1].
Figure 2. Subset map presents the position of study area with red square in the middle of West Java (A) and the study area located around Bandung Basin.
2. Materials and Methods

2.1. Materials
In this study, we used five ASTER level 1B-night observation scenes acquired by Thermal Infrared Radiometer (TIR) and six ASTER level 1B-day observation scenes acquired by Visible and Near Infrared Radiometer (VNIR). The ASTER level 1B images were selected because they were already corrected radiometrically and geometrically from the raw data [6]. Therefore, the data accuracies were considered to be higher than level 1A. The ASTER TIR images were also used because of its capability to detect objects based on their thermal characteristics such as heat, temperature, and thermal emission. The TIR images are bright on the high temperature [7]. Details of the data used are listed in Table 1.

| No | Granule             | Processing | Acquisition Date | Acquisition Time |
|----|---------------------|------------|------------------|------------------|
| 1  | AST07062018_28042   | Level 1b   | 2018-06-07       | Night            |
| 2  | AST07062018_28037   | Level 1b   | 2018-06-07       | Night            |
| 3  | AST24062016_26827   | Level 1b   | 2016-06-24       | Night            |
| 4  | AST24062016_26826   | Level 1b   | 2016-06-24       | Night            |
| 5  | AST24062016_26824   | Level 1b   | 2016-06-24       | Night            |
| 6  | AST30072018_8127    | Level 1b   | 2018-07-30       | Day              |
| 7  | AST30072018_8132    | Level 1b   | 2018-07-30       | Day              |
| 8  | AST30072018_8138    | Level 1b   | 2018-07-30       | Day              |
| 9  | AST09062017_8142    | Level 1b   | 2017-06-09       | Day              |
| 10 | AST19072014_8145    | Level 1b   | 2014-07-19       | Day              |
| 11 | AST19072014_8675    | Level 1b   | 2014-07-19       | Day              |

Field measurements of the surface temperature at 117 points and 7 points of gas concentration were aimed to verify the image analyses and geothermal features. The field measurements were concentrated on the Papandayan crater (Figure 2) with additional locations around the Bandung Basin. The gas measurements were also located at the upflow, outflow, and non-geothermal features.

2.2. Methods
In this study, we used two approaches including LST extraction from ASTER TIR night observation and field measurement for validation. The heat originated from the object is defined as kinetic temperature (\(T_{kin}\)) in this paper. We obtained \(T_{kin}\) by measuring the object directly using a contact system. In addition, the heat originated from the emission of the object is defined as radiant temperature (\(T_{rad}\)). \(T_{rad}\) could be calculated from distance with a sensor or radiometer to detect the electromagnetic radiation of an object in thermal infrared ranges 3-5 µm and 8-14 µm [8]. The \(T_{rad}\) values are usually lower than \(T_{kin}\) due to the emissivity (\(\varepsilon\)) of the objects are less than 1 [9]. The relationship between \(T_{kin}\) and \(T_{rad}\) can be expressed as follows:

\[
T_{rad} = \varepsilon^{1/4}T_{kin}
\]  

(1)

In this study, we also used the ASTER VNIR image to detect the vegetation indexes such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index 2 (EVI2). The EVI2 was developed as a solution to any satellite images that do not have a blue band such as ASTER [10]. The reason for using EVI2 is that its more responsive in detecting the variation of vegetation cover of an area, while NDVI was more responsive in detecting the chlorophyll. This process was applied to
improve the accuracy of temperature reading of LST in agreement with $T_{kin}$. From NDVI and EVI2 algorithms we obtained vegetation index with a range from -1 to 1. The index lower than 0 represents water bodies, infrastructure, and/or clouds. Index 0 and 1 represents bare land or open area and dense vegetation, respectively. The vegetation indexes were used because the TIR image could be affected by some unknown parameters such as emissivity and thermal radiation from the environment [11]. NDVI was used for estimation of Land Surface Emissivity (LSE) for correcting the emissivity of the Brightness Temperature (BT) from ASTER TIR band 13. Following the reference [12], NDVI is expressed as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$  \hspace{1cm} (2)

where NIR and RED mean reflectances at near infrared band (ASTER band 3) and visible red band (ASTER band 2), respectively. Following the reference [13], LSE could be estimated using NDVI as follows:

$$P_v = \left[\frac{NDVI - NDVI_s}{NDVI_v - NDVI_s}\right]^2$$  \hspace{1cm} (3)

$$\varepsilon_{13} = 0.968 + 0.022P_v$$  \hspace{1cm} (4)

where $\varepsilon_{13}$ is emissivity value of the ASTER band 13, $P_v$ is proportion vegetation, $NDVI_s$ is NDVI for bare soil, and $NDVI_v$ is NDVI for dense vegetation. We used emissivity of the ASTER band 13 because the ASTER TIR band 13 is the most suitable for calculating LST using Single Channel (SC) algorithm [14]. Then, the Planck’s function was used to calculate corrected LST ($T_{em}$) by incorporating the emissivity as follows:

$$T_{em} = \frac{BT}{1 + \frac{\lambda BT}{\rho} \times \ln \varepsilon_{13}}$$  \hspace{1cm} (5)

where $T_{em}$ is ASTER BT image corrected by an emissivity, $\lambda$ is the effective wavelength of the TIR band, and $\rho$ is a constant $1.438 \times 10^{-2}$ m.K. EVI2 was used to calculate the fraction of vegetation ($f_v$) and used for correcting the vegetation cover of the $T_{em}$ by [10]:

$$EVI2 = 2.5 \frac{NIR - RED}{NIR + 2.4RED + 1}$$  \hspace{1cm} (6)

Following [15], $f_v$ could be expressed as:

$$f_v = \frac{EVI2 - EVI2_s}{EVI2_v - EVI2_s}$$  \hspace{1cm} (7)

where $EVI2_s$ is dense vegetation cover and $EVI2_v$ is bare soil. $f_v$ was used to calculate the corrected $T_{em}$ by vegetation termed $T_{cveg}$ as follows:

$$T_{cveg} = 2T_{em} - (T_{em} \times f_v)$$  \hspace{1cm} (8)

The $T_{cveg}$ was a basis map to be validated with $T_{kin}$ from the field measurements [16].

The field measurements were carried out by measuring the temperature and gas concentration (SO2 and CO2). The ground temperature was measured and served as validation for $T_{cveg}$. The SO2 and CO2 gas concentrations were measured because these gases were the common gases in the upflow zone [1]. The field measurements of ground temperature and gas concentration were performed using FLIR Thermocouple and Mini Sensync Volcanic gas detector, respectively (Figure 3). Both devices measured the surface temperature and the SO2 and CO2 concentrations.
Figure 3. (A) FLIR thermocouple for measuring surface temperature; (B) Mini Sensync Volcanic gas detector to measure \( \text{SO}_2 \) and \( \text{CO}_2 \) gas concentrations.

3. Results and Discussions

3.1. Land Surface Temperature Corrected by Vegetation

The \( T_{\text{veg}} \) map (Figure 4) showed wide value range from 13.1 to 47.7°C, and this map was used as a base map for the field validation. There is a NW – SE line that appeared on \( T_{\text{veg}} \) caused by a difference acquisition time of ASTER images. Using quartile analyses, we could classify the \( T_{\text{veg}} \) data into four classes, Class-1: lower than 22°C (a normal area or cloud), Class-2: 22 – 31°C (anomaly 1), Class-3: 31 – 40°C (anomaly 2), and Class-4: higher than 40°C (surface water or infrastructures). The Class-2 and 3 were identified as anomaly 1 and 2 respectively.

A published report classified the LST into two categories, open area/infrastructures and area covered by vegetation [17]. They reported that an area with infrastructures tend to show higher temperature, as an area with vegetation cover will show low temperature reading. They corrected LST from Landsat multitemporal using emissivity without consideration to minimize vegetation factor to the calculation. According to our proposed method, we could obtain an accurate LST detection showed by the extraction value similar to \( T_{\text{kin}} \) because of the removal of the vegetation emissivity. Therefore, according to proposed method we could detect areas with high thermal anomalies.

3.2. Characterizing Upflow and Outflow from Gas Measurements

The gas measurements were carried out at the upflow (Papandayan Crater and Ciwidey Crater), outflow (Ciwalini), and non-geothermal features (ITB and Z point) zones. We classified and identified any special gases characteristics in each area (Figure 5). The gas measurements were carried out for one to two hours at each measurement point to obtain an accurate measurement. The first half hour was used to calibrate the device. The \( \text{SO}_2 \) measurements on the upflow zone tend to show a constant value due to a constant amount of \( \text{SO}_2 \) supply. As for the outflow, the measurements showed an increase with the time by the small amount supply of \( \text{SO}_2 \) reached to the ground surface. On the contrary, the non-geothermal feature showed a decrease towards near 0 due to an absence of \( \text{SO}_2 \) gas supply. Furthermore, the \( \text{SO}_2 \) reading on the upflow zone is higher than the other mentioned locations. This phenomenon agreed with the report [1] that the upflow zone tend to have richer \( \text{SO}_2 \) than the outflow zone. As for the \( \text{CO}_2 \) reading, the non-geothermal feature and outflow zones showed a little increment. We predicted that this phenomenon was caused by the organic matter near the measured point. Since the measured point...
located around the vegetated area, there was a possibility of released CO\textsubscript{2} from organic matters in the topsoil. The CO\textsubscript{2} readings on the upflow without vegetation cover tend to show a decrease. According to SO\textsubscript{2} and CO\textsubscript{2} measurements, we could identify that SO\textsubscript{2} can be more reliable than CO\textsubscript{2} to distinguish between upflow and outflow zones because the SO\textsubscript{2} gas readings were relatively independent of other material influences such as organic matter.

![Figure 4. LST corrected by vegetation (T\textsubscript{cveg}) showing the estimated temperature over the study area.](image)

3.3. Detailed Upflow Zone Identification
Detailed measurements were carried out at the Papandayan Crater (upflow zone). There were 117 points of temperature measurements and 3 points of gas measurements. These detailed measurements were aimed to validate and analyze the T\textsubscript{cveg} accuracy from ASTER TIR with field measurements. Only 42 out of 117 data can be modelled. This is due to several problems, such as the geometric and spatial resolution of the image. The measured points at upflow zone were located at high or medium T\textsubscript{cveg}. This phenomenon could be explained by the size of the manifestation that is smaller than the T\textsubscript{cveg} pixel size: one T\textsubscript{cveg} pixel covers a 15×15 m area. That is why manifestations do not always appear on high anomalous readings. The coefficient determination (R\textsuperscript{2}) value between T\textsubscript{cveg} and T\textsubscript{kin} showed a value of
around 0.61, which means $T_{\text{cveg}}$ has a high correlation with $T_{\text{kin}}$ (Figure 6). The comparison between the temperatures and gas concentrations was carried out to identify their relationship. The comparison result showed that the temperature was relatively independent of the SO$_2$ and CO$_2$ gas concentrations.

**Figure 5.** (A) The gases reading of upflow zone; (B) outflow zone; and (C) non-geothermal features.
Figure 6. Scatterplot between $T_{cveg}$ and $T_{kin}$ from 42 data showing a linear correlation with $R^2$ about 0.61.

According to the scatterplot between $T_{kin}$ and $T_{cveg}$, we obtained a regression model for a validated $T_{cveg}$ as:

$$T_{val} = (1.99 \times T_{cveg}) - 25.69$$  \hspace{2cm} (9)

where $T_{val}$ is the surface temperature model validated by the field temperature measurement $T_{kin}$. The histogram of $T_{val}$ was classified into four classes using the quartile method as follows. Class-1 with low surface temperature was distributed at $T_{val}$ lower than 14.3°C, Class-2: 14.3 – 24.8°C, Class-3: 24.8 – 35.3°C, and Class-4 higher than 35.3°C. Simplifying explanation, we defined Class-3 and 4 as high anomaly 1 and 2, respectively. A map of anomalies distribution was made from this histogram classification (Figure 7).
Figure 7. $T_{val}$ map based from histogram classification temperature of the study area, in which the green area represents anomaly reading while the brown area represents normal area. Orange dots are the gas measurements location.

4. Conclusions

The corrected $T_{cveg}$ using vegetation emissivity removal produced a surface temperature concordance to the field measurement temperature ($T_{kin}$) with $R^2$ about 0.61. This proposed method showed that $T_{cveg}$ is reliable for detecting the kinetic temperature of the ground surface. Following the correlation plot between $T_{cveg}$ and $T_{kin}$, we generated a surface temperature model $T_{val}$ as the validated temperature.

According to the SO$_2$ and CO$_2$ gas concentration measurements, the SO$_2$ concentrations showed more reliable to distinguish the upflow, outflow, and non-geothermal feature zones. The SO$_2$ gas concentration readings were relatively independent of other influences such as organic matter. The SO$_2$ at the upflow zone showed constant value with high gas concentration, the outflow zone showed an increase with low gas concentration reading, and non-geothermal features showed a decrease over time to near 0.
The upflow zone could be detected by high to medium $T_{\text{val}}$ depending on the dimension of the surface manifestations and image resolution. Therefore, the surface manifestations were located not only at high anomaly, but also medium anomaly. Regarding image resolution, a narrow surface manifestation was affected by surrounding surface temperature, which degrades the image detection.

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