Detecting the burned area in southern Kalimantan by using the sentinel-1 polarimetric SAR and landsat-8 OLI optic

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Abstract. Synthetic Aperture Radar (SAR) imageries data have turned out to be one of the essential sources for forest fire mapping, especially in tropical region since the smoke haze obstruct data acquisition by optical sensor. Despite these limitations, until now, the use of optical sensors still dominates in monitoring forest and land fires in the world. The Sentinel-1 satellites presently offer unreservedly accessible and freely available, world coverage and fast recurrent time (6–12 days), gives Sentinel-1 images the possibility to be broadly utilized for observing the Earth's surface, including forest and land fire phenomenon. However, the use of sentinel-1 data for monitoring and mapping forest and land fires in the tropics of Indonesia, is still limited and has not been widely implemented. This study investigated the use of Sentinel-1, synergy with optical Landsat-8 OLI (Operational Land Imager) data, to identify the burned area, in the tropical region of Indonesia, during 2019 fire season. A pair of Landsat-8 OLI, collected before and after fires, has been used to delineate the boundaries of sample location of burned area. Then, the difference of reflectance and Normalized Burn Ratio were analyzed. A series of Sentinel-1 images, collected before and during/after fires, has been utilized to produce the backscatter values among images. Fire incident causes landcover changes from vegetated land to bareland. This changes can affect the reflectance detected from Landsat-8 OLI. This changes also influence the backscatter recognized from SAR sensor. Then analysis of SAR backscatter on the location of the burned area detected from Landsat-8 was performed. The synergy between SAR polarimetric and optical reflected data, creates a valuable tool for identifying and interpreting burned area following a fire event.

1. Introduction

Biomass burning is widely recognized as one of the key factors influencing the succession of vegetation and carbon budgets around the world[1]. The incident has many socio-economic implications, especially in developed countries where the increasing urbanization of forest areas tends to increase accidents linked to extreme fire events[2]. Mapping of burned areas at local and regional scale using satellite images has been mostly based on medium spatial resolution data such as Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) images[2][3][4][5][6][7]. Landsat imagery is a type of satellite imagery that has been popularly used for medium scale mapping, including in burned area mapping. The main obstacle in using optical type
image data is its inability to record smoky and cloudy areas. SAR imageries data have turned out to be one of the essential sources for forest fire mapping, especially in tropical regions since the cloud and smoke haze obstruct data acquisition by optical sensors.

The Sentinel-1 satellites presently offer unreservedly accessible and freely available, world coverage and fast recurrent time (6–12 days), giving Sentinel-1 images the possibility to be broadly utilized for observing the Earth's surface, including forest and land fire phenomena. However, the use of Sentinel-1 data for monitoring and mapping forest and land fires in the tropics of Indonesia, is still limited and has not been widely implemented. This study investigated the use of Sentinel-1, synergy with optical Landsat-8 OLI (Operational Land Imager) data, to identify the burned area, in the tropical region of Indonesia, during 2019 fire season. Study location is a part of southern Kalimantan (Figure 1).

![Figure 1. Research location (red rectangle) in Southern Kalimantan. Map source: https://www.google.co.id/maps](image)

### 2. Methods

#### 2.1. Data

The optical data used were Landsat-8, path / row 118/062. The date of data acquisition was 23 March 2019 and 17 October 2019. Landsat-8 data were collected through the https://landsat-catalog.lapan.go.id/ from the The Remote Sensing Technology and Data Center of the Indonesian National Institute of Aeronautics and Space (LAPAN) (17 October 2019 data) and USGS (23 March 2019 data). The level of Landsat-8 is L1T (terrain-corrected product). The level data is corrected radiometrically and geometrically.

A pair of the L1 Detected High Resolution Dual Pro (GRD-HD) products of Sentinel-1, flight direction Descending, polarization VV and VH, were obtained from Alaska Satellite Facility through https://www.asf.alaska.edu/. The acquisition of the data were on 25 March 2019 and 15 October 2019, that were selected as they were close to Landsat-8 data acquisition time.

#### 2.2. Data Pre-processing

Landsat-8 OLI data have been converted to the spectral radiance of Top of Atmosphere (TOA). The data were converted to TOA reflectance. Instead, to convert Landsat images from TOA reflectance to surface reflectance, DOS1 (Dark Object Subtraction 1) was introduced. Sentinel-1 consists of VH and VV polarization.

The Sentinel-1 preprocessing is made up of diverse steps: 1) the orbital correction of the datum; 2) Thermal Noise Removal; 3) Callibration; 4) Speckle Filtering; 5) Terrain Correction; 6) Convert Data Type.
2.3. Delineation training samples of burned area, Normalized Difference Vegetation Index (NDVI), and Normalized Burn Ratio (NBR)

Training samples of burned area were delineated from Landsat-8 composite spectral RGB 654. The NDVI images were processed from Landsat-8 spectral band RED (band 4) and band NIR (band 5), while the NBR images were processed from Landsat-8 spectral band NIR (band 5) and SWIR (band 7)[11][12], both pre-fire (23 March 2019) and post-fire (17 October 2019) images. Then the difference of each single band reflectances, NDVI (dNDVI=NDVI post-fire - NDVI pre-fire), and NBR (dNBR=NBR post-fire - NBR pre-fire) were calculated. The mean and standard deviation of each single reflectance band, NDVI and NBR in training samples of burned area were calculated among pre-fire image, post-fire image, and also the difference image. This measurement was also performed on Sentinel-1 data among pre-fire, post-fire and the difference images, both VH and VV polarization. The separability (D-value)[13] were measured to know the selected variable that can be used to extracted burned area appropriately.

2.4. Burned area extraction

Burned area pixels were extracted using the selected variable, both using Landsat-8 and Sentinel-1 imageries by using threshold of mean + 2*Standard Deviation for Landsat-8 and mean + 1*Standard Deviation for Sentinel-1.

3. Results

3.1. The Reflectance, NDVI and NBR values of burned area pixels (pre-fire, post-fire and its changes)

Table 1 showed the Reflectance, NDVI and NBR values of burned area pixels (pre-fire, post-fire and its changes).

The results of the spectral analysis showed that burned area objects had SWIR (band 6 and 7) reflectance value higher than NIR (band 5) and and visible (band 1-4). The results of this study confirm the results of research conducted in the case of forest fires in Montana, United States [12]. Then, based on the spectral response, it can be seen that generally the biomass burning has caused high decreasing values on band 5 and there were high increasing on band 7. Both NDVI and NBR experienced decreasing values, but the NBR experienced the highest decreasing values exceed NDVI and single bands (Table 1). Previous study found that the lowest NBR values identify burned areas where vegetation has been severely damaged by fire[12]. This condition can be understood because the fire has caused a change in the condition of land cover on the surface of the earth, from previously dominated by vegetated land (forests, bushes, shrubs, plantations, agricultural land) turned into barelands that is often found traces of fires (charcoal, ash) and soil outcrops.

The results of the separability analysis also show that the NBR had the highest separability rather than others (Table 2). Because it has the highest separability, NBR is determined as the most appropriate parameter for burned area extraction from Landsat-8.

| Table 1. Reflectance, NDVI and NBR values of burned area pixels |
|---------------------------------------------------------------|
| **Pre-fire**                                                   |
| Mean | 0.0294 | 0.0304 | 0.0447 | 0.0375 | 0.2965 | 0.1296 | 0.0570 | 0.7742 | 0.6749 |
| Std.Dev | 0.0088 | 0.0088 | 0.0081 | 0.0089 | 0.0328 | 0.0078 | 0.0052 | 0.0542 | 0.0405 |
| **Post-fire**                                                  |
| Mean | 0.0419 | 0.0401 | 0.0339 | 0.0418 | 0.1192 | 0.1712 | 0.1194 | 0.4780 | -0.0009 |
| Std.Dev | 0.0049 | 0.0046 | 0.0037 | 0.0062 | 0.0188 | 0.0236 | 0.0183 | 0.0624 | 0.1159 |
### Difference

|     | 1   | 2   | 3   | 4   | 5   | 6   | 7   | NDVI | NBR  |
|-----|-----|-----|-----|-----|-----|-----|-----|------|------|
| Mean| 0.0125 | 0.0097 | -0.0108 | 0.0044 | -0.1773 | 0.0417 | 0.0624 | -0.2962 | -0.6758 |
| Std.Dev| 0.0068 | 0.0071 | 0.0073 | 0.0086 | 0.0319 | 0.0246 | 0.0170 | 0.0588 | 0.1091 |

#### Table 2. D-value

|     | 1   | 2   | 3   | 4   | 5   | 6   | 7   | NDVI | NBR  |
|-----|-----|-----|-----|-----|-----|-----|-----|------|------|
| D   | 0.911 | 0.719 | -0.912 | 0.289 | -3.434 | 1.327 | 2.653 | -2.541 | -4.321 |

3.2. **Burned area extracted from Landsat-8**

NBR is as the most appropriate parameter for burned area extraction from Landsat-8. Figure 2 showed the Landsat-8, composite spectral band RGB 654 pre-fire and post-fire and Figure 3 showed the dNBR and the extracted burned area. From Landsat-8 composite spectral band RGB 654, burned area look reddish color. Because the SWIR band (band 6 or 7) is most sensitive to burned area objects, where the band (SWIR) is inserted in the red channel, on the color appearance of this RGB composite image, burned area objects will be shown by reddish color.

#### Table 3. Sigma naught $\sigma^0$ value derived from Sentinel-1

| Pre-fire | Post-fire | Difference |
|----------|-----------|------------|
| VH       | VV        | VH         | VV         |
| Mean     | -14,302   | -17,319    | -3,018     | -1,932    |
| Std.Dev  | 1,547     | 2,050      | 1,968      | 1,943     |

3.3. **Burned area extracted from Sentinel-1**

Figure 4 showed the difference sigma naught $\sigma^0$ (25 March 2019 and 15 October 2019) and the extracted burned area from Sentinel-1 and the compilation with burned area extracted from Landsat-8. VH polarization had higher separability than VV polarization. The results of this study are consistent with the results of research conducted in the case of forest fires in Metaponto, southern Italy [14]. Thus, the VH was better used to extracted the burned area rather than VV polarization. From the picture it appears that burned area extracted from Sentinel-1 complete the burned area information on Landsat-8 that were covered by clouds and smokes haze.

#### Figure 2. Landsat-8, composite spectral band RGB 654 pre-fire and post-fire (top) and derived NBR (bottom)

(a) Landsat-8 RGB 654, 23 March 2019 (pre-fire)  
(b) Landsat-8 RGB 654, 17 October 2019 (post-fire)
Figure 3. dNBR (left) and the extracted burned area

Figure 4. The difference $\sigma^0$ and the extracted burned area
4. Conclusion

Biomass burning has caused high decreasing values on band 5 and there were high increasing on band 7. The NBR was better used to extracted burned area rather than NDVI or single spectral band. The VH polarization was better used to extracted the burned area rather than VV polarization. Burned area extracted from Sentinel-1 complete the burned area information on Landsat-8 that were covered by clouds and smokes haze. The synergy between SAR polarimetric and optical reflected data, creates a valuable tool for identifying and interpreting burned area following a fire event.

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