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Landsat 8 OLI TIRS Imagery Ability for Monitoring Post Forest Fire Changes

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ABSTRACT

The problem in this research is monitoring the forest fire disasters in South Kalimantan Province, Indonesia. One form of technology that can be applied to support the forest fire prevention activities is remote sensing satellite technology. The objective of this research is to analyze the ability of the Landsat 8 OLI TIRS for monitoring post-fire forest changes based on the ΔNBR and ΔNDVI values. The data used in this research were ΔNBR and ΔNDVI generated from Landsat 8 OLI data record from August 11 to September 6, 2017. The research showed that burned areas in South Kalimantan Province could be identified from the Landsat 8 OLI imagery based on changes on the ΔNBR and ΔNDVI values. The former burned areas during the 2017 fire season in South Kalimantan Province (August-September) were mostly found in some regency such as Banjar, Hulu Sungai Utara, Hulu Sungai Selatan, Tapin, Tanah Laut, and Banjarbaru. The Landsat 8 OLI TIRS has longer spectral bands. The use of the NBR index using the SWIR band makes the Landsat 8 OLI TIRS to be more preferred than other imagery.

Keywords: Burned Area, Landsat 8 OLI, NBR, NDVI

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INTRODUCTION

Kalimantan is extremely vulnerable to forest fires in Indonesia. The statistical data showed that 11.7 million hectares of forest in Indonesia had been burned in 1997-1998. Kalimantan had 8.1 million hectares (69%)

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of forest fires (Tacconi, 2003). Forest fires occur in Kalimantan every year. Based on data from the official website of the Indonesian Ministry of Environment and Forestry, the forest fires areas was 8,245.15 ha in 2014, 146,969.63 ha in 2015, 4,129.14 ha in 2016, and 2,745.08 ha in 2017. The forest fires in Kalimantan have a serious impact, causing a disaster mitigation effort is needed. The provision of spatial distribution information on the forest fires areas can support the mitigation effort. The information on forest fires from remote sensing data can be used for forest fires monitoring.

The use of remote sensing data to mitigate forest fire disasters in Indonesia has increased. National needs for burned areas (BA) mapping are increasingly being discussed, especially since the Reducing Emissions from Degradation and Deforestation (REDD) program (Zubaidah et al., 2017). In 2014, the Global Forest Watch online system using the data from NASA detected that Indonesia had lost 1,490,457 hectares of forest. The loss of the forest had increased from 2001 to 2014 with 745,239 hectares of forest. The causes of forest loss in Indonesia were illegal logging, forest clearing, or forest burning. Forest fires in 2014 occurred in Sumatra and Kalimantan. Forest fires in Sumatra and Kalimantan increased throughout the dry season (April-October). Provinces in Kalimantan which designated as land and forest fire-prone areas are West Kalimantan, Central Kalimantan, East Kalimantan, and South Kalimantan (Suwarsono & Parwati, 2009).

The causes of forest fires in Indonesia are 99.9% of human activities and 0.1% of natural disaster (lightning and volcanic lava). Human activities causing forest fires consist of forest conversion, vegetation combustion, exploitation of natural resources, canal construction, and Forest right. Forest fires in Kalimantan are caused by human activities, i.e. area burned for agriculture and plantation and illegal logging (Akbar et al., 2013). Fuel and fire are important factors for preparing the forests for agriculture and plantations (Adinugroho et al., 2005).

Forest fire monitoring in the field requires relatively expensive costs, time-consuming, difficult to reach, and a high danger level. The remote sensing satellite imagery is one of the methods to provide information on areas of ex-forest and forest fires quickly. Remote sensing can be done in a relatively wide and difficult area with relatively cheaper costs and high accuracy.

Application of Remote Sensing Indices in Forest Fire Detection

Remote sensing data used for analyzing burned areas are mostly in the form of optical data with various levels of spatial resolution such as MODIS, Landsat, Ikonos, and Quickbird. The burned areas can be analyzed based on changes in reflectance value, vegetation index, and NBR (Normalized Burn Ratio) (Suwarsono, 2012).

NBR is the normalized difference between the reflectance values of the near infra-red (NIR) and the short wave infra-red (SWIR) bands (Garcia & Caselles, 1991; Lutes et al., 2006), while NDVI is the normalized difference between the reflectance values of the NIR and the red bands (Bannari et al., 1995; Tucker, 1979). NBR can be used in imagery using the SWIR band, so Landsat is more likely to use the algorithm compared to MODIS which has a low spatial resolution but high spectral resolution (Vermote et al., 2015).

NBR and NDVI have the same character. For example, both indices show strongly positive values when forest features are dominated by green vegetation and high biomass. Values near zero indicate that vegetation is sparse, dead, or highly cured. Negative values indicate high soil exposure and very low vegetation cover (Lutes et al., 2006; Robichaud et al., 2007; White et al., 1996).

Delta NBR (ΔNBR) and delta NDVI (ΔNDVI) analysis increase the power to analyze changes by using imagery captured in pre-fire and post-fire dates (Lutes et al., 2006). High reflectance values for the differenced NBR and NDVI values (ΔNBR and ΔNDVI) indicate a relatively greater change from pre-fire values (reduced vegetation cover and drying of the soil surface), while the reflectance values around zero represent negligible fire impacts. Extended temporal assessments will produce strongly negative reflectance values for ΔNBR and ΔNDVI which represent vegetation growth (French et al., 2008; Lutes et al., 2006).

This research was conducted with the processing of forests images from Landsat 8 OLI TIRS satellite imagery. Remote sensing data used were forests images from Landsat 8 OLI TIRS imagery with 30 m spatial resolution and 11 spectral bands. The research data utilized the Normalized Burned Ratio (NBR) and the Normalized Difference Vegetation Index (NDVI). The consideration for the image selection was a fixed temporal resolution enabled further monitoring to be performed for wide area coverage. The analysis carried out was burned area agreement, related commission errors, related omission errors, independent commission errors, and independent omission errors. Based on the description above, it can be concluded that monitoring post-fire forest changes is very important to support disaster mitigation. Based on the background, the objective of research is to analyze the ability of the Landsat 8 OLI TIRS for monitoring post-fire forest changes based on the ΔNBR and ΔNDVI values.

METHODS

Research Location

The research was conducted in South Kalimantan Province, one of the provinces prone to land and forest fires. South Kalimantan is geographically located between 1º10'14"S - 1º21'49"S and 114º19'33"E - 116º3'28"E. South Kalimantan Province is bordered with Central and East Kalimantan Provinces. In general, lands and forests in South Kalimantan are in a wet tropical climate with an average rainfall ranging from 2000 - 3000 mm per year affected by dry and wet seasons. Figure 1 shows the research location.

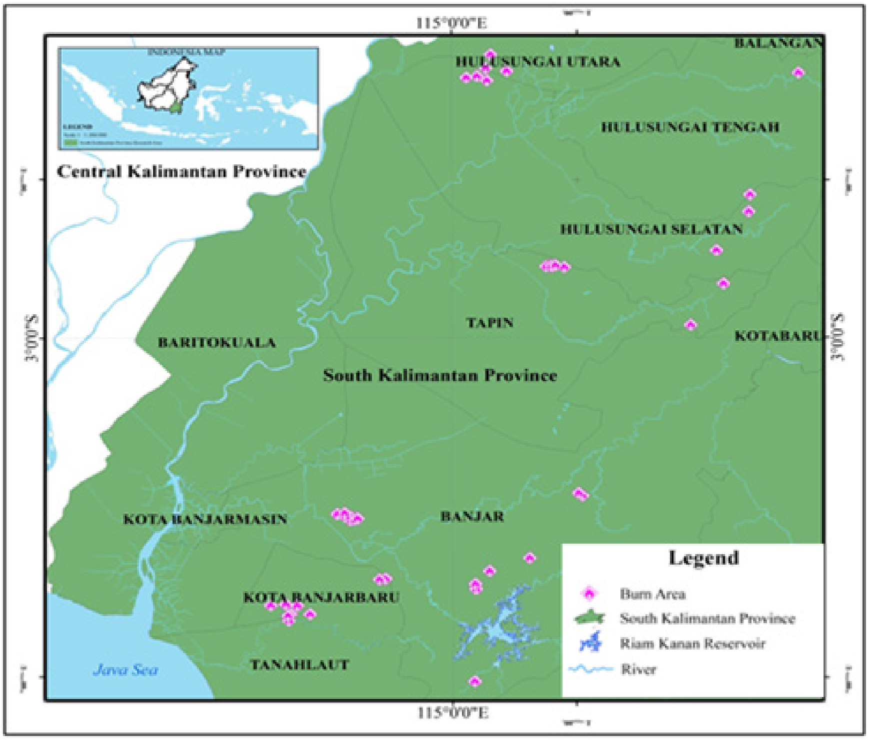


Figure 1. Forest Fires in the Research Area

The data used in this research consisted of Landsat 8 imagery data record in South Kalimantan Province in 2017, hotspot data in South Kalimantan Province in 2017 (Figure 2), and vector data on the boundaries of South Kalimantan Province. Selection of fire data on August 11 to October 6 are based on peak forest fire events. The data had fewer cloud cover than data on other dates. The software in the research comprised ArcGIS 10.3, ENVI 5.3, and Microsoft Office 2013.

Spatial Data Processing

Landsat 8 OLI data used in this research included several steps. The first step was selecting the time series hotspot data to obtain the pre- and post-fire data. The collection of Landsat 8 OLI images were adapted to the hotspot coverage data from SiPongi (sipongi.menlhk.go.id) which became the primary data in this research. The next step was processing the radiometric correction. The third step was doing cloud separation and calculation of the NBR, ΔNBR, NDVI, and ΔNDVI indices. The calculation results of ΔNBR and ΔNDVI were spatially verified through hotspot data with 80% accuracy. Then, index extraction was based on the fire location obtained from the hotspot location. The data processing and analysis carried out are described in detail as follows:

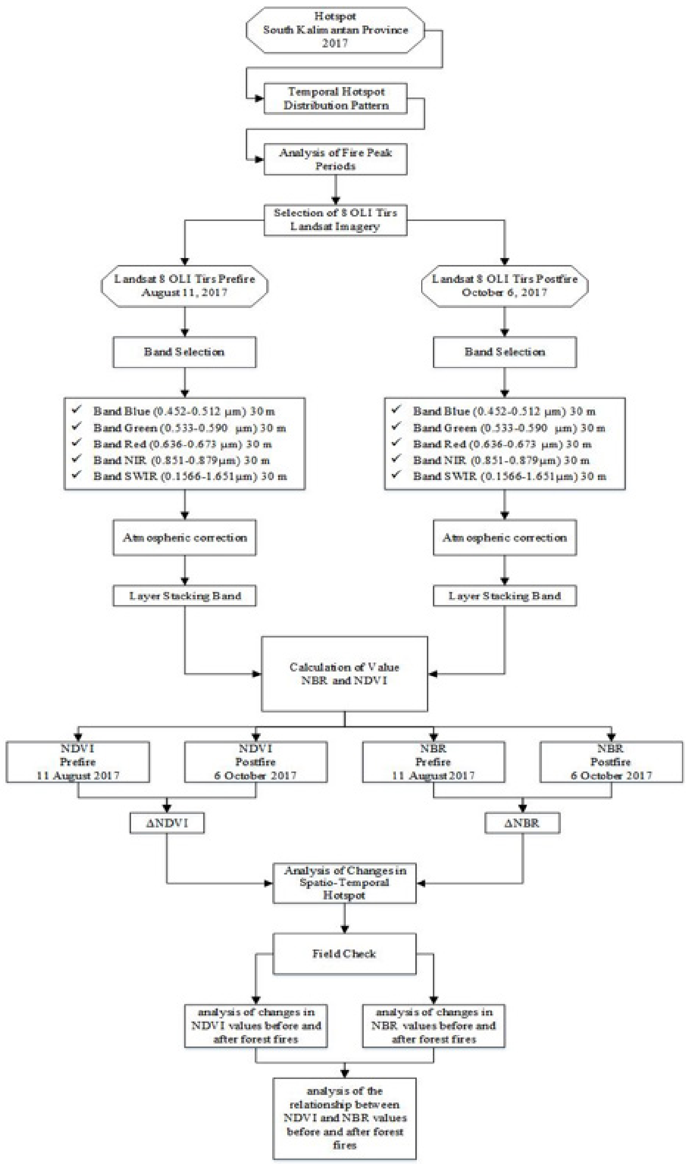


Figure 2. Flow chart

Preliminary Processing of Satellite Data. Initial data processing of Landsat 8 OLI included a radiometric correction activity. A geometric correction was done by rectification, a process to project the image into a flat plane with a map projection system having the correct direction orientation. In the rectification process, each pixel was relocated at a certain corrected position from an input image (x', y') to the output image (x, y) by doing a coordinate transformation. A geometric correction was not done on Landsat 8 images because Level 1G already had geometrically corrected images. A radiometric correction was performed to convert the digital number value to the reflectance value. Furthermore, the radiometric correction was intended to correct the pixel values by normally considering atmospheric interference factors as a major source of error, such as the location of the sun, gas absorption, and aerosol scattering in the atmosphere. Radiometric correction can be done by converting the digital number value to the reflectance value.

The general formula for the conversion of the digital number value to the spectral radiance value (USGS, 2016) is as follows:

L = (DN/A) + B..........................[1]

Where:

L = spectral radiance (W / m2 / sr / Im)

DN = Digital Number value Landsat 8 OLI data

A = Gain value of absolute calibration

B = Offset value of absolute calibration

A, B = can be seen in the file header

The general formula for the conversion of the spectral radiance value to the reflectance value is:

$$r = \frac{\pi d^2 \mathrm{L}}{ESUN \cos \Theta} \qquad \text{..........................[2]}$$

Where:

r = Reflectance (value 0-1)

N = 3.14152

d = Earth-Sun distance = (1-0.01674 cos (0.9856 (Julian date - 4))) 2

L = spectral radiance

ESUN = Mean exoatmospheric solar irradiance

q = Solar zenith angle in radiance

In optical satellite data such as Landsat 8 OLI images, cloud cover is an obstacle for obtaining information, especially in land and forest fires, from satellites within Kalimantan area. Satellite images are sometimes covered by clouds and smoke haze. Cloud cover becomes a barrier because optical energy cannot penetrate it (Richards, 2009). Cloud cover cannot be removed because when it is removed, it will not replace the value that corresponds to the current surface conditions. Cloud cover is also difficult to mask (cloud masking) because some hotspot areas are areas located on high cloud cover. Cloud cover is feared to contribute in covering the hotspot to be observed. It is strongly recommended for further research to use satellite imagery able to overcome various limitations in this research such as high cloud cover. Radar imagery can be used for research on forest fires and burned land (Rodionova, 2016; Sugardiman, 2007) but it is necessary to pay attention to the wavelength used by the radar imagery as well as access and availability to the public. Radar imagery likely to be used with open access is Sentinel-1 because it uses a C-band wavelength with a width of 250 km coverage (ESA, 2014).

Processing of NBR and NDVI Indices. The normalized burn ratio in Landsat 8 images were calculated for the classification of the burned area. The burned area was identified based on the threshold value (t) where the threshold used to determine the burned area was μ-1σ. The general formulas used to obtain the NBR (Key & Benson, 1999) and NDVI values (Huete et al., 2002) are as follows:

$$NBR=\frac{NIR-SWIR}{NIR+SWIR} \quad [3]$$

$$NDVI=\frac{NIR-RED}{NIR+RED} \quad [4]$$

Where:

NIR = Reflectance Band 5 from Landsat 8 OLI

SWIR = Reflectance Band 6 from Landsat 8 OLI

RED = Reflectance Band 4 from Landsat 8 OLI

Separation of Burned Forests and Unburned Forests

Separation of burned and unburned forests is (Key et al., 1999; Viedma et al., 1997):

$$\Delta NBR=NBR_{(pre\text{-}fire)} - NBR_{(post\text{-}fire)} \quad [5]$$

$$\Delta NDVI=NDVI_{(pre\text{-}fire)} - NDVI_{(post\text{-}fire)} \quad [6]$$

Assumptions used: burned forests have a higher vegetation index in pre-fire than post-fire, so the delta index is positive (positive ΔNBR or ΔNDVI).

Burned Area Identification

The burned area was identified based on the μ-1σ threshold model. A pixel (Xij) is stated as the burned area if it meets the following requirements:

$$Xij<t_{BA} \quad [7]$$

Where t_{BA} is the threshold value of a pixel stated as the burned area

RESULTS

Hotspot Distribution Analysis

The number of hotspots in the research area was 42 points occurred in August-September 2017. These hotspots were used as research samples based on the lack of cloud and cloud shadow disturbances on Landsat 8 OLI images, making them be a representative sample for hotspots in this research. Table 1 presents the hotspot locations in this research.

Table 1

Hotspot locations in South Kalimantan Province

Regency	District	Village	Hotspot
Banjar	Aranio	Belangian	1
Banjar	Aranio	Benua Riam	1
Banjar	Aranio	Rantau Bujur	2
Banjar	Aranio	Tiwingan Lama	1
Banjar	Astambul	Minggu Raya	2
Balangan	Awayan	Ju'uh	1
North Hulu Sungai	Babirik	Pajukungan	1
North Hulu Sungai	Babirik	Sungai Papuyu	2
Tapin	Bakarangan	Gadung	6
Banjarbaru City	Banjar Baru	Sungai Besar/Sungai Ulin	2
TanahLaut	Bati – Bati	Pandahan	1
South Hulu Sungai	North Daha	Hakurung	3
Banjar	Karang Intan	East Awang Bangkal	1
Banjarbaru City	Landasan Ulin	Guntung Payung	1
Banjarbaru City	Landasan Ulin	West Landasan Ulin	1
Banjarbaru City	Landasan Ulin	Central Landasan Ulin	2
Banjarbaru City	Landasan Ulin	East Landasan Ulin	2
South Hulu Sungai	Loksado	Hulu Banyu	1
South Hulu Sungai	Loksado	Lumpangi	1
South Hulu Sungai	Loksado	Muara Ulang	1
Banjar	Martapura	Akar Bagantung Ulu	1
Banjar	Martapura	Sungai Batang Ilir	2
Banjar	Martapura	Tangkas	2
Banjar	Pengaron	Alimukim	1
Banjar	Pengaron	Antaraku	1
Tapin	Piani	Batung	1
Tapin	Piani	Pipitak Jaya	1
Number of hotspots			42

Based on hotspot samples in the research area during August 5, 2017- September 21, 2017, the highest incidence occurred on September 8, 2017 of 11 hotspots with a confidence level of > 80% in the research location (Figure 3). The lowest incidence occurred on August 27, 2017, September 1, 2017 and September 20, 2017 of 1 hotspot with a confidence level of > 80% in the research location (Figure 3).

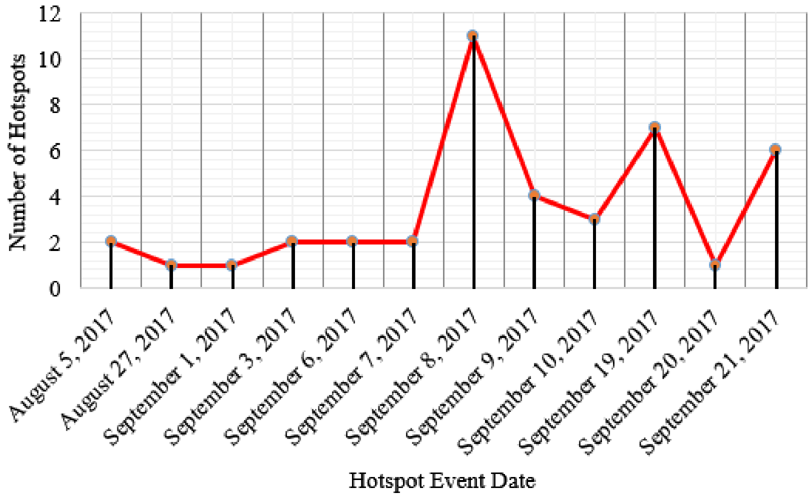


Figure 3. Number of hotspots in South Kalimantan Province

In Figure 4, the true color composite of Landsat 8 OLI images in time series on August 11, 2017 and October 6, 2017 in South Kalimantan Province is presented. Based on visual analysis on the time series of the true color composite, it can be seen that there was a change in the forests from green vegetation to exposed soil on August 11, 2017 and October 6, 2017 in the areas marked with a red circle.

Based on the Landsat 8 OLI images in time series shown in Figure 4, the pre- and post-fire forest vegetation on August 11, 2017 and October 6, 2017 can be obtained. Figure 5 presents the pre- and post-fire data.

Details of the pre- and post-fire forest conditions can be seen in Figure 5. To understand the hotspot conditions in 2017 in the research location, Figure 6 shows the results of the hotspot plot on August-October 2017 in the research location. The hotspot plot is marked with a red point. The hotspot distributions from Modis Terra/Aqua, NOAA19, and LPN-NPP data are presented below. That period was the period of forest fires around the research location.

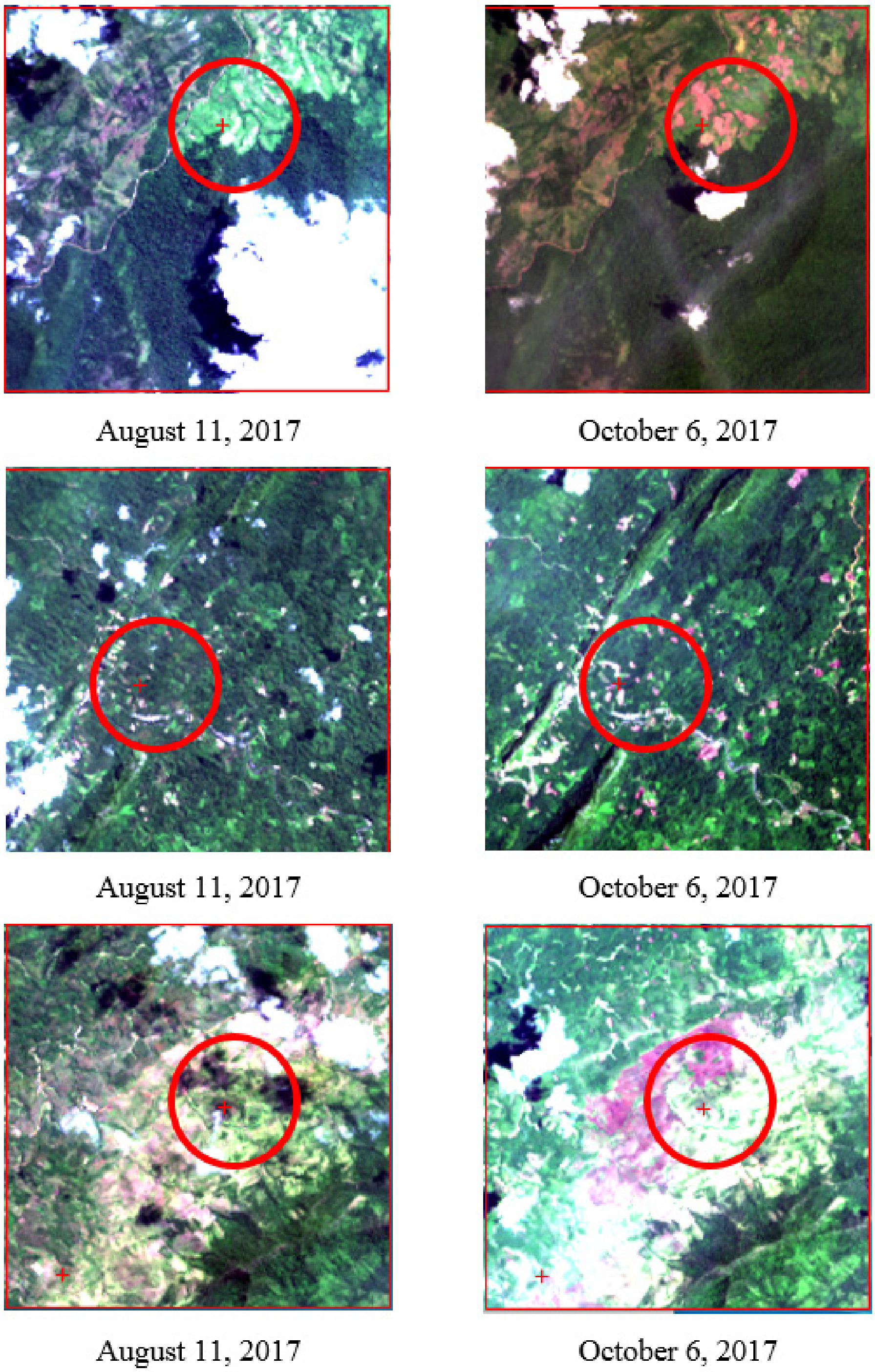
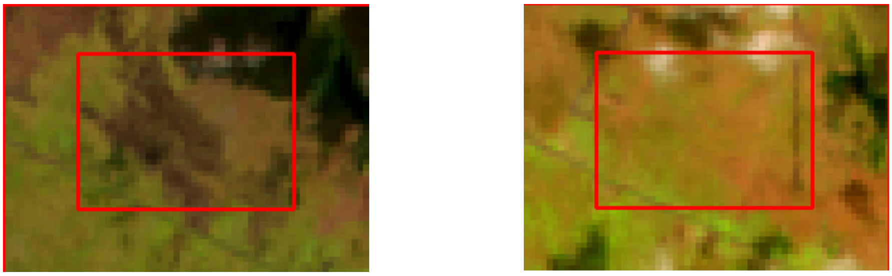


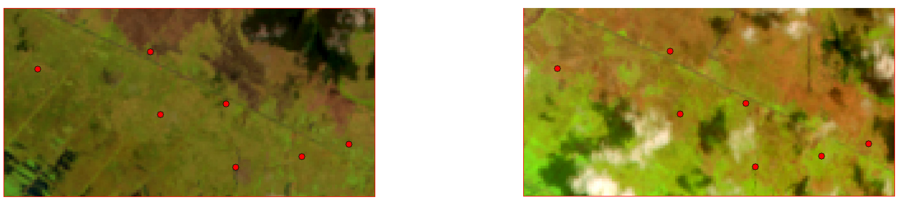
Figure 4. True color composite of the Landsat 8 OLI images in time series on August 11, 2017 and October 6, 2017 in the research location



Pre-fire condition
on August 11, 2017

Post-fire condition
on September 6, 2017

Figure 5. Pre- and post-fire forest conditions from Landsat 8 data record on August 11, 2017 and September 6, 2017



Pre-fire forests
August 11, 2017

Post-fire forests
September 6, 2017

Figure 6. Overlay of pre-fire hotspot data on August 11, 2017 and post-fire hotspot data on September 6, 2017 (Red hotspot is a hotspot sample from Modis Terra/Aqua, NOAA19, and LPN-NPP)

Analysis of Changes in Spatio-Temporal Hotspots

Based on hotspot data, Landsat 8 OLI data, and visual analysis at the research location, ΔNBR and ΔNDVI analysis were divided into 2 parts: pre-fire data on August 11, 2017 and post-fire data on September 6, 2017. Spatio-temporal hotspots in the research location changed in value during the pre-fire and post-fire process. The pre-fire NBR values were relatively higher compared to the post-fire NBR values. In Figure 7, the ΔNBR graphic shows that the difference between pre-fire and post-fire conditions tended to be dominated by positive ΔNBR values. The number of positive ΔNBR values was 32 samples. Negative ΔNBR values indicated increased vegetation productivity following a fire. The number of negative ΔNBR values was 10 samples. The highest ΔNBR value was 0.229954596 in Raya Village, Aranio District, Banjar Regency, while the lowest ΔNBR value was -0.212095 in Gadung Village, Aranio District, Banjar Regency. The graphic of NBR value changes before and after land and forest fires is shown in Figure 7 and the graphic of ΔNBR is presented in Figure 8.

The pre-fire NDVI values were relatively higher than the post-fire NDVI values. In Figure 8, the ΔNDVI graphic shows that the difference between pre-fire and post-fire conditions tended to be dominated by positive ΔNDVI values which indicated more severe damage. The number of positive ΔNDVI values was 35 samples. Negative ΔNDVI values indicated an increased vegetation productivity following a fire. The number of

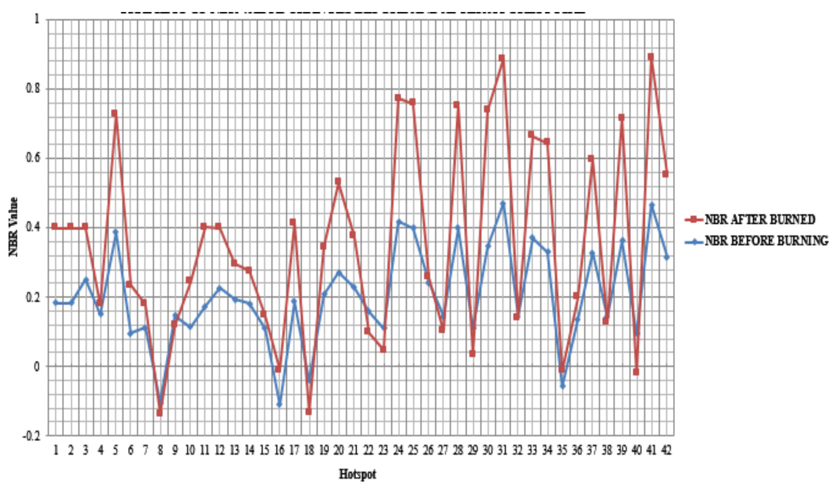


Figure 7. The Graphic of NBR value changes before and after forest fires

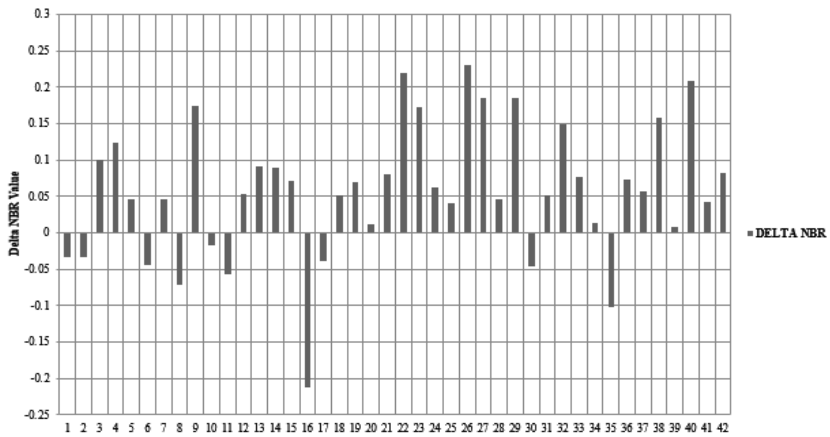


Figure 8. The ΔNBR values in the research area

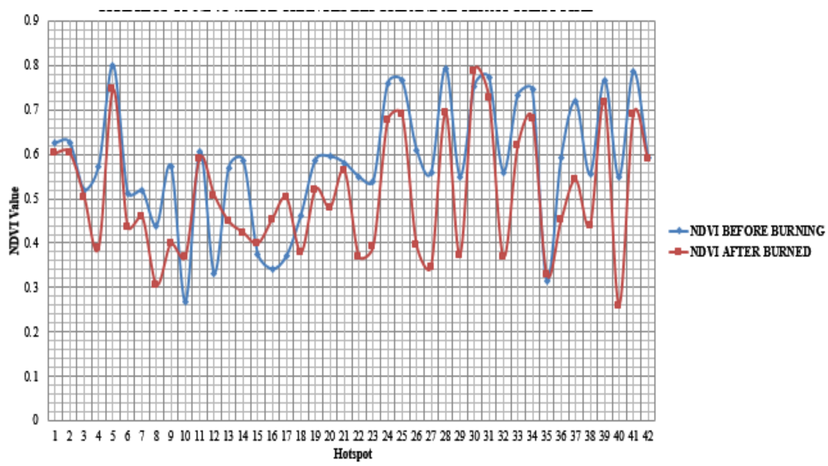


Figure 9. The graphic of NDVI value changes before and after forest fires

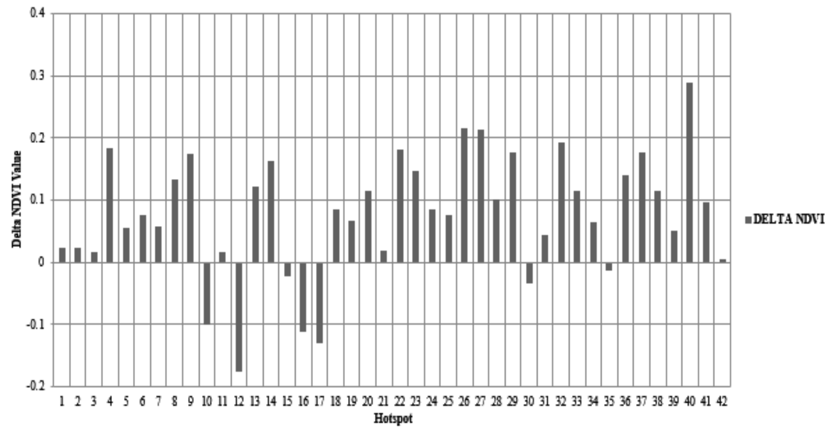


Figure 10. The ΔNDVI values in the research area

negative ΔNDVI values was 7 samples. The highest ΔNDVI value was 0.287900001 in East Landasan Ulin Village, Landasan Ulin District, Banjarbaru City, while the lowest ΔNDVI value is -0.175138026 in Akar Bagantung Ulu Village, Babirik District, North Hulu Sungai Regency. The graphic of NDVI value changes before and after land and forest fires is shown in Figure 9 and the graphic of the ΔNDVI values is presented in Figure 10.

DISCUSSION

Through processing and analysis, the ΔNBR and ΔNDVI methods can be an alternative way to monitor forest burning. The pre-fire NDVI values were relatively higher than the post-fire NDVI values. Some studies also show similar results. van Leeuwen et al. (2010) research indicated changes in the post-fire NDVI value. Tonbul et al. (2016) research indicated that the NDVI value in the burned area had decreased from 0.48 to 0.17.

The pre-fire NBR values were relatively higher compared to the post-fire NBR values. The research conducted by (Parwati et al., 2012) showed that NBR had a higher value in pre-fire rather than in post-fire condition. This statement is in accordance with the results obtained in this research. Thus, the use of NBR index is very appropriate for studying the post-fire forest condition.

Some studies have been able to classify the burn severity level (Kumar et al., 2008). Classification accuracy of burn severity can be produced and improved by increasing the spatial resolution of images (e.g. SPOT 5, Sentinel 1, and Sentinel 2) (Kumar et al., 2008). Landsat 8 OLI/TIRS has longer spectral bands. The use of the NBR index using the SWIR band makes Landsat 8 OLI/TIRS more preferred than other imagery without the SWIR band (Vermote et al., 2015). Landsat 8 OLI/TIRS is very suitable for monitoring forest fires.

CONCLUSIONS

Monitoring of the burned forest in South Kalimantan (the research area) had been carried out based on the analysis of Landsat 8 OLI data through the ΔNBR and ΔNDVI indices. Both NDVI and NBR had higher values in pre-fire than in post-fire conditions. On the burned forests, the ΔNBR index showed a higher value than the ΔNDVI index, while in forests without burning activity, the ΔNBR index value was lower than ΔNDVI. It showed that the burned forests had a lower humidity level than the unburned forests. The forests' conditions can be represented well through the ΔNBR index using the SWIR band which is very sensitive to vegetation water content. Further development from this research is to identify the threshold value of the burned forests.

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