

Capability of Sentinel-1 Synthetic Aperture Radar polarimetric change detection for burned area extraction in South Kalimantan, Indonesia

by Syam'ani Syam'ani

Submission date: 19-May-2023 02:15PM (UTC+0700)

Submission ID: 2096908771


File name: Syamani_2020_IOP_Conf._Ser._Earth_Environ._Sci._500_012004.pdf (2.74M)

Word count: 6102

Character count: 33525

PAPER · OPEN ACCESS

Capability of Sentinel-1 Synthetic Aperture Radar polarimetric change detection for burned area extraction in South Kalimantan, Indonesia

 To cite this article: Syam'ani 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **500** 012004

View the [article online](#) for updates and enhancements.

Capability of Sentinel-1 Synthetic Aperture Radar polarimetric change detection for burned area extraction in South Kalimantan, Indonesia

Syam'ani

Spatial Data Infrastructure Development Centre (PPIDS), University of Lambung Mangkurat, Banjarbaru, South Kalimantan, Indonesia

e-mail: syamani.fhut@ulm.ac.id

Abstract. Burned area extraction from optical imageries often has a major problem, that is the presence of atmospheric particles. A potential alternative for burned area extraction is using SAR imageries, those are relatively free of atmospheric interference. The purpose of this research was to explore change detection capabilities of Sentinel-1 SAR polarimetry for burned area extraction. The imagery used is dual-polarized Sentinel-1 (VV,VH). A number of polarimetric transformation methods are applied for the purpose of change detection. Those are, single cross-polarized log ratio, single co-polarized log ratio, dual polarized combination log ratio, dual polarized multiple log ratio, and dual polarized ratio log ratio. For comparison, the Relativized Burn Ratio (RBR) method was applied to the Sentinel-2 MSI imagery. The Otsu thresholding is then applied to separate the burned area and the unburned area. The results of the research showed that the single cross-polarized log ratio ($\ln(\sigma^0_{VH_{11}}/\sigma^0_{VH_{22}})$) transformation method was the most accurate method. This method has an overall accuracy of 88.7665% (Kappa 0.7567). It is more accurate than Sentinel-2 RBR, which has an overall accuracy of 81.8470% (Kappa 0.6383). Cross validation between Sentinel-1 SAR change detection and Sentinel-2 RBR does not show a significant correlation. The highest correlation coefficient achieved is only 0.25. This shows that burned area extraction between change detection from SAR imageries and RBR from optical imageries has a different mechanism. SAR change detection tends to detect changes in surface roughness, while NIR-based RBR tends to extract changes in leaf chlorophyll conditions.

1. Introduction

South Kalimantan is one of the provinces on the Kalimantan island or the Borneo island, Indonesia. Like the tropics in general, South Kalimantan experiences two seasons in a year, those are the rainy season and the dry season. If there is a long dry season, such as in 2014, 2015, and 2018, both pristine areas and cultivation areas, both experience the risk of forest and land fire disasters. This disaster of forest and land fires is of course a special concern for the local government, even the Indonesian central government.

Some burned areas can experience natural restoration or revegetation by themselves. Other areas, such as cultivation areas, will be restored to vegetation through planting activities carried out by the community themselves. However, certain areas, such as forests or peatlands, must restore themselves for a considerable period of time. So that areas like this need special handling, such as forest and land rehabilitation activities.

Of course, to be able to carry out forest and land rehabilitation activities, including direct handling after forest and land fire disasters, accurate burned area information is needed. During this time, the burned area can be extracted from several sources with various methods. The easiest is the visual delineation of



multispectral optical images such as Landsat 8 OLI. Or you can also directly download the burned area information from the MODIS product MCD45A1 (1) or MCD64A1 (2).

Visual delineation is an inefficient method of burned area extraction process, besides its consistency which is still to be questioned. While the burned area product MCD45A1 or MCD64A1 from MODIS have a coarse resolution (500 meters). Some burned areas that are small enough are not legible by MCD45A1/MCD64A1, in some cases, the estimate can also be overestimated (3). For the efficiency of burned area extraction, we usually use quantitative method, which are using the burned area indices, such as, Burn Area Index (BAI) (Martin, 1998) (AJK1), Normalized Burn Ratio (NBR) (4), (5), (6), Burned Area Index Modified-SWIR (BAIMs) (7), Normalized Burn Ratio Thermal (NBRT) (8), Burned Area Index Modified-LSWIR (BAIML) (9), Relativized Burn Ratio (10), or Burned Area Index for Sentinel-2 (BAIS2) (11).

Burned area indices such as BAI, NBR, NBRT, and others, are applied to multispectral optical imageries. Some methods, such as NBRT, even have to use thermal band imagery. In the process of extracting burned areas quantitatively using optical images, two images are needed at different times. One image during the rainy season or the end of the rainy season, and one image at the end of the dry season. This is to capture changes that occur on the land surface, specifically changes in vegetation features due to forest and land fires.

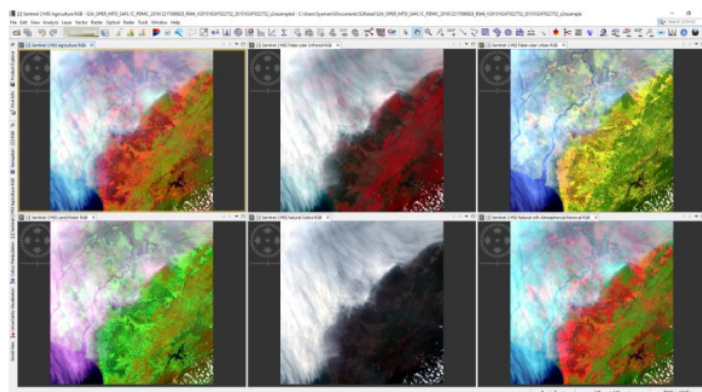


Figure 1. Sentinel-2A imagery (with various color composites) in a part of South Kalimantan acquired on October 24, 2015

High resolution optical imageries such as the Sentinel-2 Multispectral Instrument (MSI), are able to provide information on the distribution of burned areas with detailed spatial levels and high geometric accuracy. However, like optical imageries in general, always have problems with atmospheric interference. For tropical regions such as South Kalimantan in particular, and Indonesia in general, during the rainy season, multispectral optical imageries are always decorated with fog, clouds, and water vapor. While during the dry season, especially in the event of forest and land fires, the optical imageries will be covered by dust and even smoke generated from forest and land fires themselves. Figure 1 shows an example of Sentinel-2 imagery covered by fire smoke. In such conditions, quantitative burned area extraction from optical imageries less effective.

Given the availability of clean multispectral optical imageries is very difficult to obtain. We need an alternative remote sensing data source that is free of atmospheric interference, for the purposes of extracting geospatial information from the burned area. A potential alternative for burned area extraction is using Synthetic Aperture Radar (SAR) imageries, those are relatively free of atmospheric interference.

Before the Sentinel-2 MSI multispectral optical satellite was launched into orbit, the Sentinel-1 SAR satellite already existed, which was orbit in 2014. Sentinel-1 carries a microwave active sensor. As we all know, microwave sensors can capture backscattering in a long range of electromagnetic wavelengths. So that the view of this sensor is able to penetrate atmospheric particles such as fog, clouds, water vapor, dust, and smoke. The presence of SAR sensors from Sentinel-1 is a very interesting alternative for imaging interests in areas that are vulnerable to atmospheric disturbances, such as the tropics. What's more, the availability of images can be obtained for free on the internet.

Sentinel-1 SAR imagery can be used for a number of purposes, one of which is to extract burned areas. Previously, there were several studies on the use of SAR imageries for extraction of burned areas. Either use Sentinel-1 or other SAR sensors. Among them are what are done by (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (23), and (26).

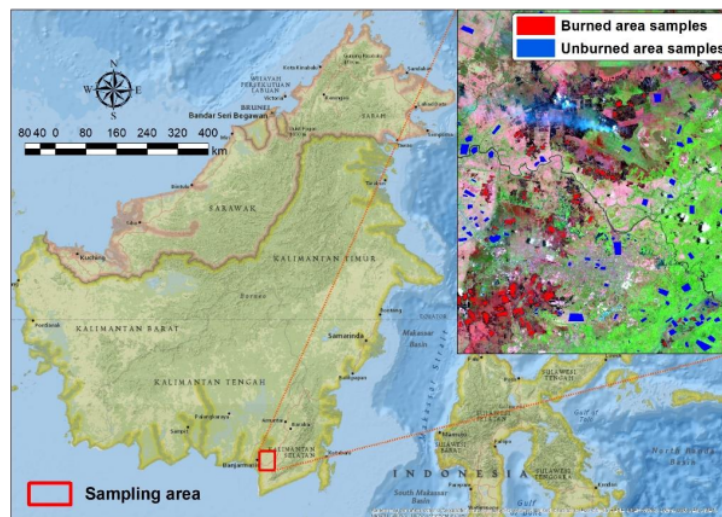


Figure 2. Research location and accuracy assessment samples

The purpose of this research was to explore change detection capabilities of Sentinel-1 SAR polarimetry for burned area extraction. This research was conducted in parts of the Province of South Kalimantan (Figure 2), by taking examples of cases of forest and land fires that occurred in the region in 2018. The sample area was chosen at the location of the most severe fires during the dry season of 2018. And this region has indeed been subscribed to experiencing fires every long dry season. The selected sample area has an area of 200,000 hectares. Another consideration in choosing this sample region is that the cleanest area of atmospheric disturbance in Sentinel-2 imageries is taken.

2. Research Methods

2.1. The Imageries Used and Pre-processing

The SAR imagery used is dual-polarized C-band Sentinel-1 (VV, VH). By taking sample of Sentinel-1 multitemporal imageries those acquired on July 11, 2018 (S1A_IW_GRDH_1SDV_20180711T215946_20180711T220011_022752_027750_0683) and October 3, 2018 (S1A_IW_GRDH_1SDV_20181015T215950_20181015T220015_024152T220015_024152_02A435

_0554). Where July is the end of the rainy season (pre-fire), at the same time the beginning of the dry season. While October is the end of the dry season (post-fire).

Sentinel-2 imageries taken must be coherence to the acquisition time of Sentinel-1. However, taking exactly the same two acquisition times from two different remote sensing platforms, is really difficult. What's more we are required to look for Sentinel-2 imageries that are the cleanest of atmospheric disturbances. So that the Sentinel-2 imageries that can be obtained in this study acquired on July 10, 2018 (S2A_MSIL1C_20180710T022551_N0206_R046_T50MKB_20180710T055823) and October 3, 2018 (S2B_MSIL1C_20181003T022549_N0206_R046_T50MKB_20181003T064351).

The Sentinel-1 image processing using Sentinel-1 Toolbox (S1TBX). Sentinel-1 SAR imagery calibrated into normalized Radar Cross Section (RCS), Sigma Nought (σ^0). Then multilooked and co-registered using SRTM 1-arc second, so that the spatial resolution becomes 20 meters. This process is implemented on each multitemporal Sentinel-1 imageries. Furthermore, both multitemporal SAR imageries are stacked, and multitemporal speckle filtered. The multitemporal speckle filtering used is Intensity-Driven Adaptive-Neighborhood (IDAN) (27). Multitemporal IDAN speckle filtering was choice because according to (28) research result, this filter technique is the best speckle filter.

The level 1C Sentinel-2 MSI imageries calibrated into top of canopy reflectance (level 2A) using Sen2Cor (29, 30). Sentinel-2 spatial resolution then resampled into 20 meters. Cloud masked was also applied to the multitemporal Sentinel-2 imageries. The Sentinel-2 image processing using Sentinel-2 Toolbox (S2TBX). Either S1TBX, S2TBX, or Sen2Cor, all three are integrated in the European Space Agency (ESA) Sentinel Application Platform (SNAP) application.

2.2. Log Ratio Change Detection and Polarimetric Transformation

The change detection method used in this study is pixel-based, which is more specific using the log ratio method. The log ratio method was chosen because this method is the simplest method. Besides this method was integrated in the SNAP software used in this study.

Various polarimetric transformation models were determined as candidate models in this study, namely single cross-polarized log ratio, single co-polarized log ratio, dual polarized combination log ratio, dual polarized multiple log ratio, and dual polarized ratio log ratio. The form of the equations can be seen as follows:

Single Cross-polarized Log Ratio (SCrPLR):

$$SCrPLR = \ln \left(\frac{\sigma_{VHt1}^0}{\sigma_{VHt2}^0} \right) \quad (1)$$

Single Co-polarized Log Ratio (SCPLR):

$$SCPLR = \ln \left(\frac{\sigma_{VVt1}^0}{\sigma_{VVt2}^0} \right) \quad (2)$$

Dual Polarized Combination Log Ratio (DPCLR):

$$DPCLR = \ln \left(\frac{\sigma_{VHt1}^0 + \sigma_{VVt1}^0}{\sigma_{VHt2}^0 + \sigma_{VVt2}^0} \right) \quad (3)$$

Dual Polarized Multiple Log Ratio (DPMLR):

$$DPMLR = \ln \left(\frac{\sigma_{VHt1}^0 \sigma_{VVt1}^0}{\sigma_{VHt2}^0 \sigma_{VVt2}^0} \right) \quad (4)$$

Dual Polarized Ratio Log Ratio (DPRLR):

$$DPRLR = \ln \left(\frac{\sigma_{VHt1}^0 / \sigma_{VVt1}^0}{\sigma_{VHt2}^0 / \sigma_{VVt2}^0} \right) \quad (5)$$

Where:

- σ_{VHt1}^0 : Sigma nought calibrated pre-fire Sentinel-1 VH polarization
- σ_{VHt2}^0 : Sigma nought calibrated post-fire Sentinel-1 VH polarization
- σ_{VVt1}^0 : Sigma nought calibrated pre-fire Sentinel-1 VV polarization
- σ_{VVt2}^0 : Sigma nought calibrated post-fire Sentinel-1 VV polarization

Figure 3 clearly show steps for Sentinel-1 SAR image processing using SNAP software.

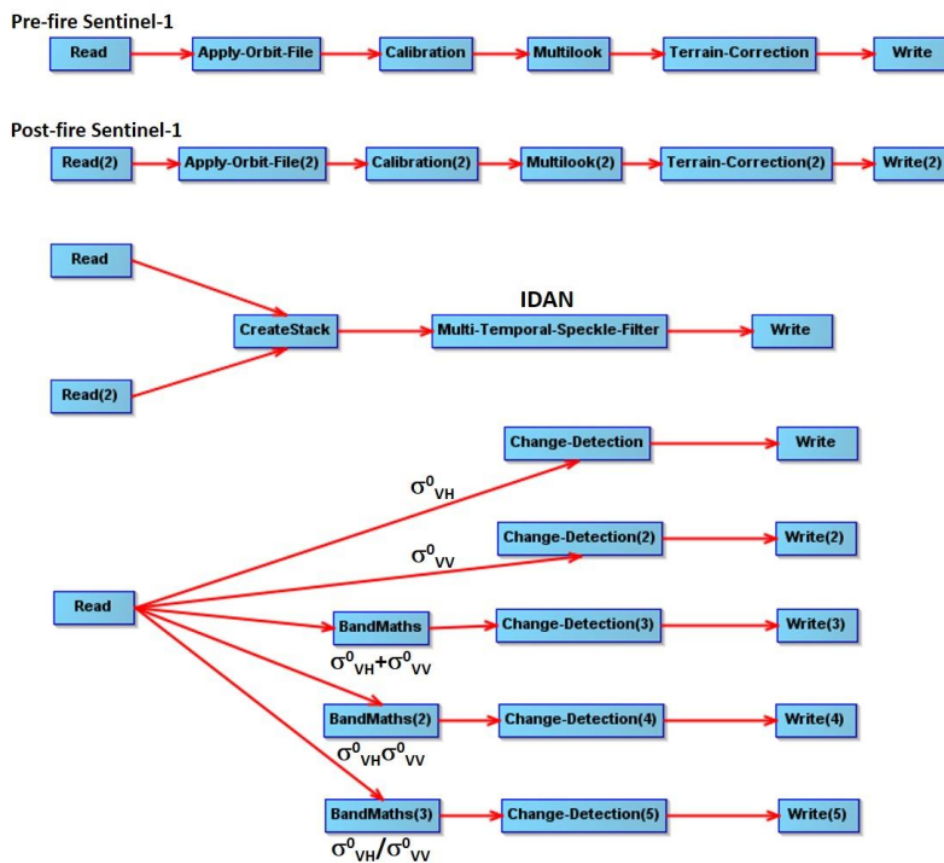


Figure 3. Sentinel-1 processing steps

2.3. Relativized Burn Ratio

Relativized Burn Ratio (RBR) is a comparative model in this study. RBR formulated by (10) as follows:

$$\frac{NBR_{prefire} - NBR_{postfire}}{NBR_{prefire} + 1.001} \quad (6)$$

Normalized Burn Ratio (NBR) is formulated by (4), (5), and (6) as follows:

$$NBR = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \quad (7)$$

Where:

ρ_{NIR} : Near infrared band (band 8) of Sentinel-2 MSI

ρ_{SWIR} : Shortwave infrared band (band 12) of Sentinel-2 MSI

2.4. Otsu Thresholding

Polarimetric change detection results, including RBR, will each produce an image with certain pixel values. To separate the burned area pixel value and the unburned area pixel value, we use the Otsu thresholding method (31). The Otsu thresholding assumes that data (pixel value) is univariate gaussian bimodal. So that after being separated using the Otsu thresholding, the burned area and unburned area will have a univariate gaussian unimodal distributed pixel value. In this study, the Otsu thresholding process was implemented automatically using Fiji is just ImageJ (Fiji) free open source software (32), (33).

2.5. Accuracy Assessment and Cross Validation

The accuracy assessment of the burned area extraction results using the confusion matrix (34), (35). The number of samples/region of interest (ROI) is taken for each burned area and unburned area. The selection of sample areas was carried out by a knowledge-based method based on the visual appearance of the burned area on Sentinel-2 imagery. The total sample burned area is more than 60,000 pixels, and the total sample unburned area is more than 100,000 pixels, as shown in Figure 2.

Furthermore, to test the correlation between polarimetric change detection from SAR and RBR images from Sentinel-2 imageries, cross validation was implemented in the burned area ROI using linear and nonlinear regression methods. If the confusion matrix aims to test the ability of SAR polarimetric change detection in separating between burned area and unburned area, then cross validation aims to provide a description of the ability of burned area extraction from SAR images, whether later it can be used to classify fire severity as RBR from Sentinel-2 imagery or not.

3. Results and Discussion

Most of the forest and land fires in South Kalimantan occur in wetland areas. With the type of landcover/landuse of rice fields, moor, plantations, swamps shrubs and bushes, swamp forests, and peatlands. The rest of the fires occur in dryland shrubs and bushes, secondary dryland forests, to dryland agriculture and community-owned dryland plantations. Figure 4 show the spatial distribution of burned area in a part of South Kalimantan in 2018. Either burned area from Sentinel-2 RBR or burned area from Sentinel-1 polarimetric log ratio change detection.

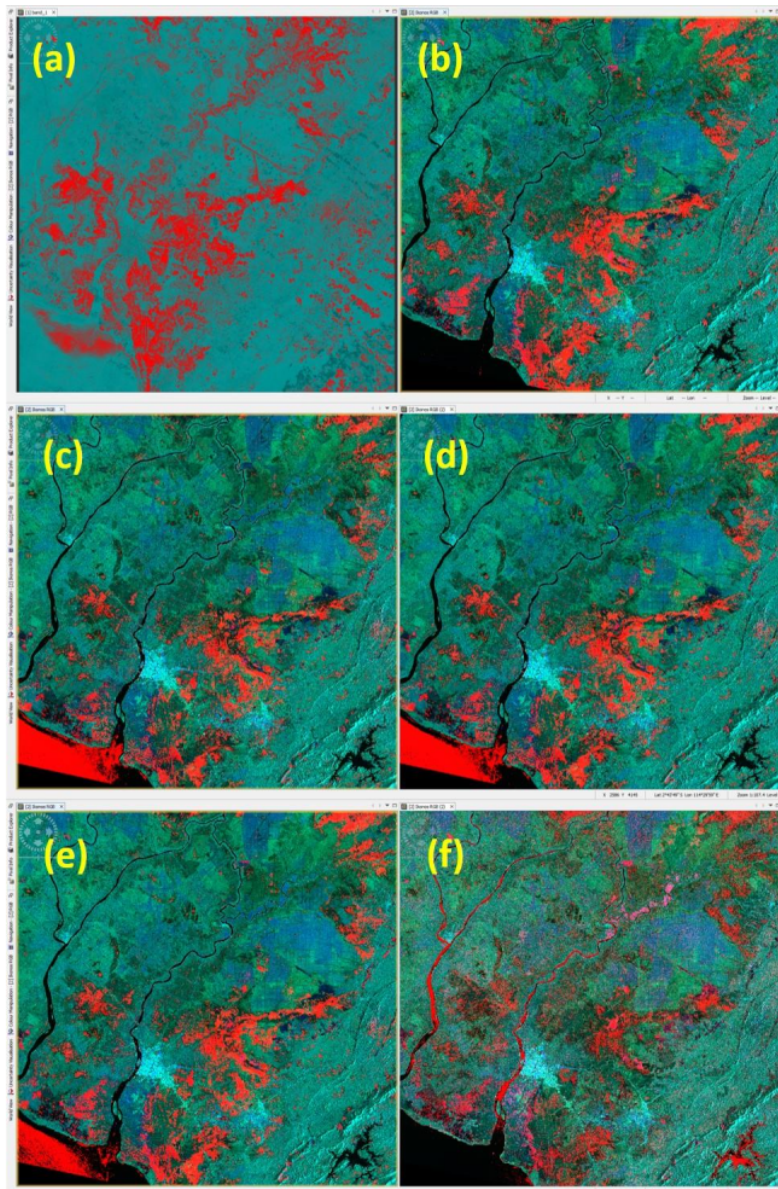


Figure 4. Comparison of burned area from Sentinel-2 RBR and Sentinel-1 polarimetric log ratio change detection (red color for burned area)

Figure description:

(a) is Sentinel-2 RBR, while (b), (c), (d), (e), and (f) are RGB composites. Where (b) is SCrPLR, $VH_{\text{post-fire}}$, $VV_{\text{post-fire}}$, (c) is SCPLR, $VH_{\text{post-fire}}$, $VV_{\text{post-fire}}$, (d) is DPCPLR, $VH_{\text{post-fire}}$, $VV_{\text{post-fire}}$, (e) is DPMLR, $VH_{\text{post-fire}}$, $VV_{\text{post-fire}}$, and (f) is DPRLR, $VH_{\text{post-fire}}$, $VV_{\text{post-fire}}$.

Accuracy assessment result, as shown in Table 1, shows that the Sentinel-1 polarimetric change detection method with the SCrPLR transformation model, is generally the most accurate method for burned area extraction. If seen from OA which is more than 88%, kappa, PA, and UA, it can be stated that this method is able to recognize the burned area effectively and is relatively able to avoid detection of burned area errors. However, the PA is still less accurate compared to Sentinel-1 RBR. This means that RBR's ability to identify burned areas is better than SCrPLR. The results of the research which was conducted in the case of fires in Indonesia in 2015 (26), and also using Sentinel-1 imagery was resulted OA 84%. They use the change temporal matrices, such as (VH_{t1}/VH_{t2}) and $(VV_{t1}-VV_{t2})$. Next, to extract the burned area they were using object-based image analysis approach.

Table 1. Accuracy assessment result

No.	Models	Equations	Otsu	OA (%)	Kappa	BA PA (%)	BA OE (%)	BA UA (%)	BA CE (%)
1	SCrPLR*	$\ln\left(\frac{\sigma_{VH_{t1}}^0}{\sigma_{VH_{t2}}^0}\right)$	0.44	88.7665	0.7567	80.94	19.06	88.24	11.76
2	SCPLR *	$\ln\left(\frac{\sigma_{VV_{t1}}^0}{\sigma_{VV_{t2}}^0}\right)$	0.40	81.0942	0.5878	69.05	30.95	78.18	21.82
3	DPCLR*	$\ln\left(\frac{\sigma_{VH_{t1}}^0 + \sigma_{VV_{t1}}^0}{\sigma_{VH_{t2}}^0 + \sigma_{VV_{t2}}^0}\right)$	0.40	83.7850	0.6486	74.15	25.85	81.15	18.85
4	DPMLR*	$\ln\left(\frac{\sigma_{VH_{t1}}^0 \sigma_{VV_{t1}}^0}{\sigma_{VH_{t2}}^0 \sigma_{VV_{t2}}^0}\right)$	0.83	86.0020	0.6963	76.79	23.21	84.60	15.40
5	DPRLR*	$\ln\left(\frac{\sigma_{VH_{t1}}^0 / \sigma_{VV_{t1}}^0}{\sigma_{VH_{t2}}^0 / \sigma_{VV_{t2}}^0}\right)$	0.02	63.8938	0.2885	72.46	27.54	51.45	48.55
6	RBR**	$\frac{NBR_{prefire} - NBR_{postfire}}{NBR_{prefire} + 1.001}$	0.15	81.8470	0.6383	93.32	6.68	69.20	30.80

*Proposed candidate models

**Comparative model

BA = Burned Area

OA = Overall Accuracy

PA = Producer's Accuracy

OE = Omission Error

UA = User's Accuracy

CE = Commission Error

Another model of Sentinel-1 polarimetric transformation that is quite competitive is DPMLR. In general, the accuracy of this model is below the SCrPLR, but it is still more accurate than RBR. The high accuracy of the SCrPLR model is understandable. Considering the disasters of forest and land fires, burning objects are almost entirely vegetation features. According to (36), the volumetric features of vegetation have the highest backscatter on cross-polarized (VH). So that changes in vegetation features due to fire can be detected properly on the SCrPLR.

Based on the results of the accuracy comparison, the SCPLR accuracy is lower than the SCrPLR. Furthermore, combining VV with VH, both combination, multiplication, especially ratio, tends to have an effect that will reduce accuracy. Still according to (36), VV polarization has the strongest backscatter on a double bounce feature like a building, and has a backscatter stronger than VH on surface features, such as asphalt surfaces, barelands, or water surfaces. This is what causes changes in the water level feature to be detected as the burned area of the SCPLR, where this does not occur in the SCrPLR, as shown in Figure 4. So SCrPLR is the most effective model for avoiding errors in detecting burned areas in the body of the water.

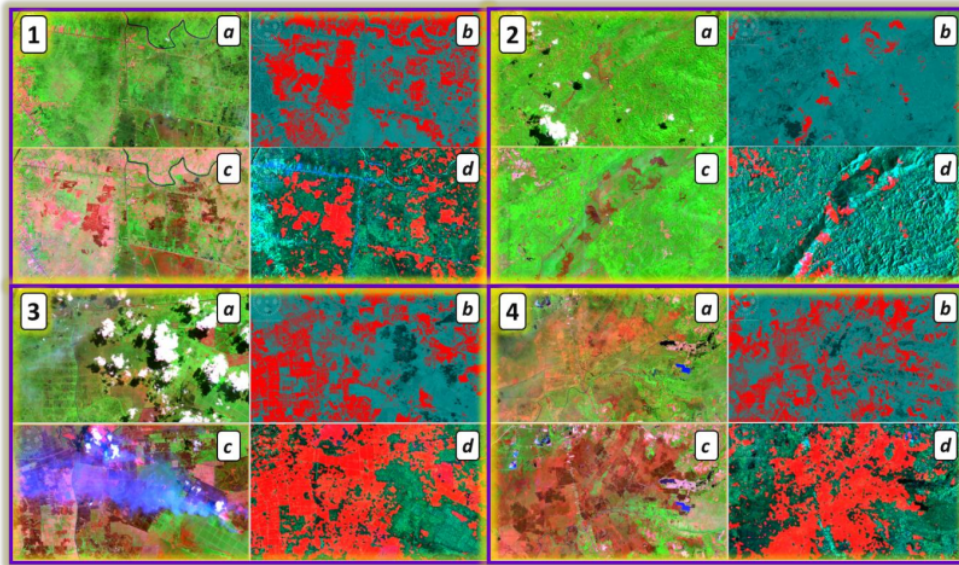


Figure 5. Visual comparison of Sentinel-2 pre-fire, Sentinel-2 post-fire, RBR, and SCrPLR (red color for burned area)

Figure description:

Burned area in rice fields

Burned area in dryland forests and dryland shrubs and bushes

Burned area in plantations

Burned area in swamp shrubs and bushes

Sentinel-2 pre-fire RGB composite 11-8-4

Sentinel-2 post-fire RGB composite 11-8-4

Sentinel-2 RBR

Sentinel-1 SCrPLR

Figure 5 shows a visual comparison between Sentinel-2 pre-fire, Sentinel-2 post-fire, Sentinel-2 RBR, and Sentinel-1 SCrPLR. In this picture the extraction of the burned area is shown on several different features that are burning. It is seen that there are visually clear differences between the extraction results of RBR and SCrPLR. Visually, it appears that on some features, RBR tends to overestimate. This guess is also confirmed by the accuracy test results in Table 1, where OA RBR is more than 30%, which means overestimation. Although the ability of RBR to identify burned areas is better than SCrPLR, this can be seen from the PA which is more than 90%.

The ability of SCrPLR to identify the burned area is below RBR, this can be seen from the PA which is around 80%, below the RBR which is more than 90%. However, the UA is the highest among all models. This makes the SCrPLR the most effective model in preventing burned area error detection. Of course, there are still a number of possible errors in detecting the burned area in the SCrPLR. And the possibility of errors like this is partly not experienced by RBR. For more details, some potential errors in detection of burned areas can be seen in Figure 6.

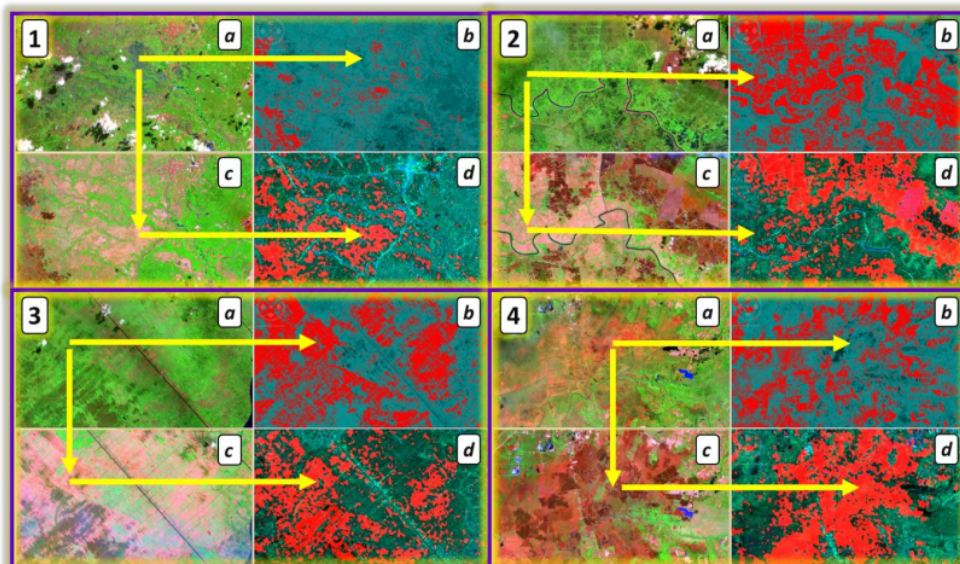


Figure 6. Potential error of burned area extraction

Figure description:

1. Dried swamp was not detected as burned area by Sentinel-2 RBR, but was detected as burned area by Sentinel-1 polarimetric change detection.
2. Post-harvest dried straws detected as burned area by Sentinel-2 RBR, but it was not detected as burned area by the Sentinel-1 polarimetric change detection.
3. Dried rice fields and dried straws, detected as burned areas both by Sentinel-2 RBR and by Sentinel-1 polarimetric change detection.
4. Pre-fire dried swamp shrubs and bushes. The swamp which dries out the water and the scrub vegetation that dries out its leaves before it burns, then burns, was not detected as burned area by Sentinel-2 RBR, but was detected as burned area by Sentinel-1 polarimetric change detection.

- a. Sentinel-2 pre-fire RGB composite 11-8-4
- b. Sentinel-2 post-fire RGB composite 11-8-4
- c. Sentinel-2 RBR
- d. Sentinel-1 SCrPLR

In both Figure 5 and Figure 6, we only took SCrPLR as a comparison sample with RBR. This is because the SCrPLR is the most accurate model, as discussed earlier. In Figure 6, the SCrPLR detects a dry swamp as a burned area, which is not experienced by RBR. So in cases like this, RBR is superior. However, when the swamp that dries is accompanied by drying out large amounts of vegetation, the SCrPLR and RBR both detect it as the burned area, even though the area is not burned at all.

Sentinel-1 SCrPLR excels when faced with two cases, namely when the dense vegetation then dries, and the vegetation is dried before burning and then burning. This can be easily understood, because RBR is a NIR-based model. So that the burned area detection depends on changes in chlorophyll content in the leaves. Whereas SAR imagery tends to detect surface roughness. When the vegetation leaves dry, although not burned as post-harvest dried straws, RBR will detect it as the burned area, because the vegetation loses chlorophyll. However, because the dried vegetation does not cause a significant change

in surface roughness, the SAR polarimetric change detection relatively does not detect it as the burned area. The problem that is similar, but with the opposite condition, occurs when the vegetation was dried first before burning, and then burns. In this study experienced by swamp shrub and bush features. In cases like this, of course there is no change in chlorophyll in the leaves, because the chlorophyll has disappeared before it burns. So that RBR does not detect a burned area. However, because the burned dry vegetation causes changes to the surface roughness, SAR polarimetric change detection actually detects it as the burned area.

Figure 7 shows burned area extraction result from full swath of Sentinel-1 SCrPLR. In the picture it can be seen that some actual areas are not burned (based on field knowledge), but are detected as burned areas. The areas in question are non-fire deforestation, such as logging activities, mining, harvesting, land clearing, and so on. Of course, this kind of detection error will be experienced by all automatic-quantitative burned area extraction methods, including by RBR. Especially for SAR polarimetric change detection, our suspected detection error also comes from the speckle effects, which are commonly found in SAR imageries. Although in this study speckle filtering has been implemented. Of course, for practical purposes, a little manual correction must be done, by eliminating small burned area polygons, both due to noise in SAR imagery, and non-fire deforestation. With this technique, it is believed that it will be able to increase the accuracy of the map of the burned area produced.

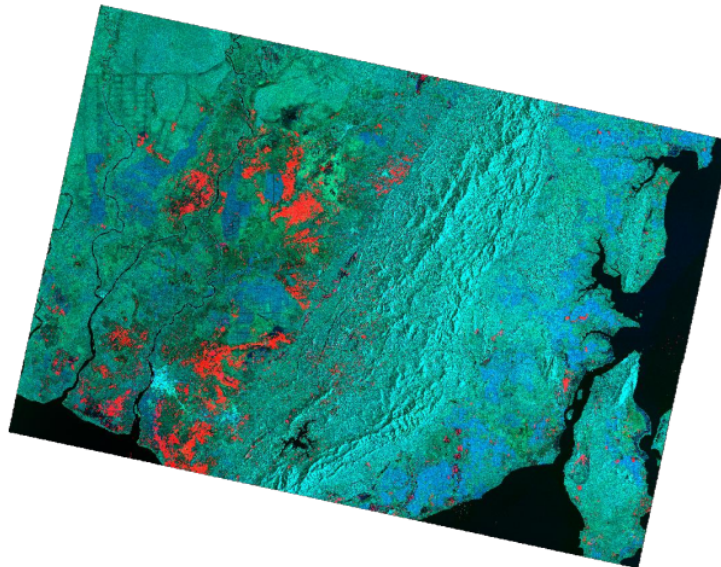


Figure 7. Full swath of Sentinel-1 RGB composite (SCrPLR, $VH_{\text{post-fire}}$, $VV_{\text{post-fire}}$) show the burned area (red color for burned area)

The other disadvantages of SCrPLR are predicted to occur in the case of very low severity burns, such as in grassland fires. This is due to the ability of the Sentinel-1 SAR C band sensor that can penetrate several centimeters under the grass surfaces. So that burned area on grasslands have the potential not to be detected as the burned area by the SCrPLR, because the SAR sensor does not capture a change in surface roughness. Conversely, when there is a change in surface roughness without fire (no loss of chlorophyll), the SCrPLR will potentially detect it as the burned area. This can happen, for example, in cutting down trees, leaving behind bushes and thickets of living beneath them. So that the chlorophyll feature remains before and after logging trees. In such cases, NIR-based RBR can actually identify correctly, that there is no fire in that area.

SAR polarimetric change detection is quite competitive with RBR in extracting burned areas, even the fact is more accurate based on the results of this research. However, statistically the extracted burned area from SAR polymetric change detection does not have a significant correlation with RBR. This can be seen from the results of cross validation between Sentinel-1 log ratio burned area and Sentinel-2 RBR burned area, as shown in Figure 8. Where the highest correlation coefficient achieved is only about 0.25. Based on this fact, we can consider that, SAR polarimetric change detections are need their own burn severity classification, because they cannot take the classification interval directly from RBR.

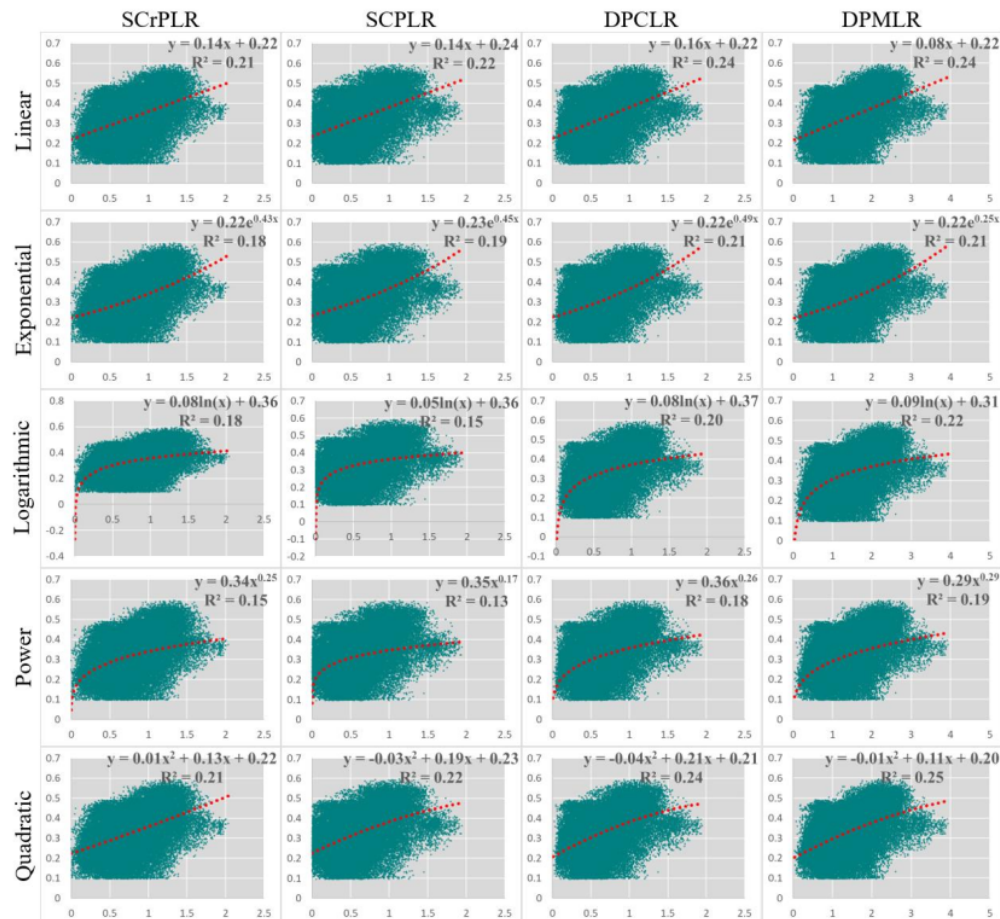


Figure 8. Cross validation between Sentinel-1 log ratio burned area and Sentinel-2 RBR burned area (y for Sentinel-2 RBR and x for Sentinel-1 polarimetric change detection)

However, the SAR polatimetric change detection has not been able to directly classify the burn severity using the existing standard burn severity classification, as possessed by NBR or RBR. So to be able to classify burn severity in the burned area of the SAR polarimetric change detection, in the future more comprehensive research is needed. In Figure 8 we exclude the DPRLR model from statistical cross validation, because the OA was too low. So this model will be impossible to use further in the burned area extraction.

We also have further predictions that the SAR-based burned area extraction will be far more effective, and will provide more accurate results in fires on drylands. Especially in the case of forest fires or tree vegetation with a level of very high severity burn. This is based on the fact that SAR imagery is greatly affected by surface changes in water features, so SAR-based burned area extraction becomes less effective for fires in wetlands. In addition, the ability to penetrate Sentinel-1's C band is several centimeters on the surface of vegetation features, demanding changes in surface roughness with sufficient intensity, only to be detected as the burned area.

4. Conclusions

Quantitative burned area extraction, both Sentinel-2 RBR and Sentinel-1 polarimetric change detection, works by capturing changes in surface features at certain time intervals. In this case, the feature change in question are the vegetation features. Because the fuel of forest and land fires is mainly vegetation cover. RBR is NIR-based, so the changes that are captured by RBR are actually changes in the features of chlorophyll or vegetation leaves. So that if the vegetation loses leaves, in other words it burns, it can easily be detected by RBR. While Sentinel-1 polarimetric change detection is based on changes in surface roughness. So that when the vegetation burns, there will be a change in the surface roughness.

In general, we recommend a single cross-polarized (VH) log ratio model for burned area extraction. This is because based on the results of this research, this model is the most effective. Of course, with all the shortcomings. For practical purposes later, the accuracy of this model can be improvised by eliminating small polygons error detection of burned areas. Furthermore, because the Sentinel-1 polarimetric change detection does not have a significant statistical correlation with Sentinel-2 RBR, in the future more comprehensive research is needed to make the polarimetric log ratio classification interval, to classify burn severity of Sentinel-1 SAR imageries. SAR-based burned area extraction will also be far more effective, and will provide more accurate results in fires on drylands. Especially in the case of forest fires or tree vegetation with a level of very high severity burn. In contrast, SAR-based burned area extraction is less effective in wetland areas.

5. Acknowledgements

This research was funded by the Spatial Data Infrastructure Development Center (PPIDS) of Lambung Mangkurat University. We sincerely thank for the European Space Agency for providing all the Sentinel-1 SAR and Sentinel-2 MSI imageries freely and the ESA SNAP free open source software. We also thank for the Remote Sensing and Geographic Information System Laboratory, Faculty of Forestry, Lambung Mangkurat University, for facilitating the image processing in this research.

6. References

- [1] Boschetti L, Roy D, Hoffmann AA. MODIS Collection 5 Burned Area Product-MCD45. User's Guide, Ver. 2009;2.
- [2] Giglio L, Boschetti L, Roy DP, Humber ML, Justice CO. The Collection 6 MODIS burned area mapping algorithm and product. *Remote sensing of environment*. 2018;217:72-85.
- [3] Tsela PL, van Helden P, Frost P, Wessels K, Archibald S, editors. Validation of the MODIS burned-area products across different biomes in South Africa. 2010 IEEE International Geoscience and Remote Sensing Symposium; 2010: IEEE.
- [4] García ML, Caselles V. Mapping burns and natural reforestation using Thematic Mapper data. *Geocarto International*. 1991;6(1):31-7.

- [5] Key C, Benson N. Landscape assessment: ground measure of severity, the Composite Burn Index; and remote sensing of severity, the Normalized Burn Ratio. FIREMON: Fire effects monitoring and inventory system. 2005;2004.
- [6] Koutsias N, Karteris M. Burned area mapping using logistic regression modeling of a single post-fire Landsat-5 Thematic Mapper image. *International Journal of Remote Sensing*. 2000;21(4):673-87.
- [7] Trigg S, Flasse S. An evaluation of different bi-spectral spaces for discriminating burned shrub-savannah. *International Journal of Remote Sensing*. 2001;22(13):2641-7.
- [8] Holden Z, Smith A, Morgan P, Rollins M, Gessler P. Evaluation of novel thermally enhanced spectral indices for mapping fire perimeters and comparisons with fire atlas data. *International Journal of Remote Sensing*. 2005;26(21):4801-8.
- [9] Martín MP, Gómez I, Chuvieco E. Burnt Area Index (BAIM) for burned area discrimination at regional scale using MODIS data. *Forest Ecology and Management*. 2006(234):S221.
- [10] Parks S, Dillon G, Miller C. A new metric for quantifying burn severity: the relativized burn ratio. *Remote Sensing*. 2014;6(3):1827-44.
- [11] Filipponi F, editor BAIS2: Burned Area Index for Sentinel-2. Multidisciplinary Digital Publishing Institute Proceedings; 2018.
- [12] Liew S, Kwoh L, Padmanabhan K, Lim O, Lim H. Delineating land/forest fire burnt scars with ERS interferometric synthetic aperture radar. *Geophysical Research Letters*. 1999;26(16):2409-12.
- [13] Kasischke ES, Bourgeau-Chavez LL, Johnstone JF. Assessing spatial and temporal variations in surface soil moisture in fire-disturbed black spruce forests in Interior Alaska using spaceborne synthetic aperture radar imagery—Implications for post-fire tree recruitment. *Remote Sensing of Environment*. 2007;108(1):42-58.
- [14] Tanase MA, Santoro M, Wegmüller U, de la Riva J, Pérez-Cabello F. Properties of X-, C-and L-band repeat-pass interferometric SAR coherence in Mediterranean pine forests affected by fires. *Remote Sensing of Environment*. 2010;114(10):2182-94.
- [15] Goodenough DG, Chen H, Richardson A, Cloude S, Hong W, Li Y. Mapping fire scars using Radarsat-2 polarimetric SAR data. *Canadian Journal of Remote Sensing*. 2012;37(5):500-9.
- [16] Jenkins L, Bourgeau-Chavez L, French N, Loboda T, Thelen B. Development of methods for detection and monitoring of fire disturbance in the Alaskan tundra using a two-decade long record of synthetic aperture radar satellite images. *Remote Sensing*. 2014;6(7):6347-64.
- [17] Kalogirou V, Ferrazzoli P, Della Vecchia A, Fomelis M. On the SAR backscatter of burned forests: A model-based study in C-band, over burned pine canopies. *IEEE Transactions on Geoscience and Remote Sensing*. 2014;52(10):6205-15.
- [18] Tanase MA, Santoro M, Aponte C, de la Riva J. Polarimetric properties of burned forest areas at C-and L-band. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 2013;7(1):267-76.
- [19] Kurum M. C-band SAR backscatter evaluation of 2008 Gallipoli forest fire. *IEEE Geoscience and Remote Sensing Letters*. 2015;12(5):1091-5.
- [20] Stroppiana D, Azar R, Calò F, Pepe A, Imperatore P, Boschetti M, et al. Integration of optical and SAR data for burned area mapping in Mediterranean regions. *Remote Sensing*. 2015;7(2):1320-45.
- [21] Tanase M, Kennedy R, Aponte C. Radar Burn Ratio for fire severity estimation at canopy level: An example for temperate forests. *Remote Sensing of Environment*. 2015;170:14-31.
- [22] Verhegghen A, Eva H, Ceccherini G, Achard F, Gond V, Gourlet-Fleury S, et al. The potential of Sentinel satellites for burnt area mapping and monitoring in the Congo Basin forests. *Remote Sensing*. 2016;8(12):986.
- [23] Belenguer-Plomer MA, Tanase MA, Fernandez-Carrillo A, Chuvieco E, editors. Insights into burned areas detection from Sentinel-1 data and locally adaptive algorithms. *Active and Passive Microwave Remote Sensing for Environmental Monitoring II*; 2018: International Society for Optics and Photonics.
- [24] Engelbrecht J, Theron A, Vhengani L, Kemp J. A simple normalized difference approach to burnt area mapping using multi-polarisation C-Band SAR. *Remote Sensing*. 2017;9(8):764.

- [25] Martinis S, Caspard M, Plank S, Clandillon S, Haouet S, editors. Mapping burn scars, fire severity and soil erosion susceptibility in Southern France using multisensor satellite data. 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS); 2017: IEEE.
- [26] Lohberger S, Stängel M, Atwood EC, Siegert F. Spatial evaluation of Indonesia's 2015 fire-affected area and estimated carbon emissions using Sentinel-1. *Global change biology*. 2018;24(2):644-54.
- [27] Vasile G, Trouvé E, Lee J-S, Buzoiu V. Intensity-driven adaptive-neighborhood technique for polarimetric and interferometric SAR parameters estimation. *IEEE Transactions on Geoscience and Remote Sensing*. 2006;44(6):1609-21.
- [28] Medasani S, Reddy GU. Analysis and Evaluation of Speckle Filters for Polarimetric Synthetic Aperture Radar (PolSAR) Data. *International Journal of Applied Engineering Research*. 2017;12(15):4916-27.
- [29] Louis J, Debaecker V, Pflug B, Main-Knorn M, Bieniarz J, Mueller-Wilm U, et al., editors. Sentinel-2 sen2cor: L2a processor for users. *Proceedings of the Living Planet Symposium, Prague, Czech Republic*; 2016.
- [30] Main-Knorn M, Pflug B, Louis J, Debaecker V, Müller-Wilm U, Gascon F, editors. *Sen2Cor for Sentinel-2. Image and Signal Processing for Remote Sensing XXIII*; 2017: International Society for Optics and Photonics.
- [31] Otsu N. A threshold selection method from gray-level histograms. *IEEE transactions on systems, man, and cybernetics*. 1979;9(1):62-6.
- [32] Schneider CA, Rasband WS, Eliceiri KW. NIH Image to ImageJ: 25 years of image analysis. *Nature methods*. 2012;9(7):671.
- [33] Schindelin J, Rueden CT, Hiner MC, Eliceiri KW. The ImageJ ecosystem: An open platform for biomedical image analysis. *Molecular reproduction and development*. 2015;82(7-8):518-29.
- [34] Stehman SV, Czaplewski RL. Design and analysis for thematic map accuracy assessment: fundamental principles. *Remote sensing of environment*. 1998;64(3):331-44.
- [35] Rossiter D. Statistical methods for accuracy assessment of classified thematic maps. *Technical Note Enschede: International Institute for Geo-information Science & Earth Observation (ITC)*. 2004.
- [36] Meyer F. Spaceborne Synthetic Aperture Radar: Principles, Data Access, and Basic Processing Techniques in *The Synthetic Aperture Radar (SAR) Handbook: Comprehensive Methodologies for Forest Monitoring and Biomass Estimation: SERVIR Global Science*; 2019. 21-63 p.

Capability of Sentinel-1 Synthetic Aperture Radar polarimetric change detection for burned area extraction in South Kalimantan, Indonesia

ORIGINALITY REPORT

17%

SIMILARITY INDEX

15%

INTERNET SOURCES

14%

PUBLICATIONS

9%

STUDENT PAPERS

MATCH ALL SOURCES (ONLY SELECTED SOURCE PRINTED)

10%

★ Abdi Fithria. " Habitat suitability modelling of Pasak Bumi Jack.) in Riam Kanan conservation forest zone using Sentinel-2 biophysical parameters ", IOP Conference Series: Earth and Environmental Science, 2020

Publication

Exclude quotes On

Exclude matches Off

Exclude bibliography On