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Research Article

Utilizing Sentinel-2 Data for Mapping Burned Areas in Banjarbaru Wetlands, South Kalimantan Province

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Sentinel-2 imagery can identify forest and land fires in underground parts, surface fires, and crown fires. The dNBR and RBR spectral indices on Sentinel-2 images proved accurate in identifying. This study analyzed the index value for burned area mapping in wetland areas using Sentinel-2 imagery data in 2019 and hotspot data from the MODIS data. The indices used to identify the burned area and the severity of the fire was the differenced normalized burn ratio (dNBR) and relativized burn ratio (RBR). Visual validation tests were performed by comparing RGB composite images to check the appearance before and after combustion with dNBR and RBR results. The dNBR value accuracy was 91.5%, and for a kappa, the accuracy was 89.58%. The RBR accuracy was 92.9%, and the kappa accuracy was 0.91. The results confirmed that in the Banjarbaru area, RBR was more accurate in identifying burned areas than dNBR; both indices can be used for burned area mapping in wetland areas.

1. Introduction

Forest and land fires repeat yearly during the dry season and significantly impact the environment, humans, ecosystems, and wildlife [1]. Land fires also cause air pollution that contributes to global climate change [2]. Fire monitoring employing adequate technology is crucial to tackling repeated fires in large areas. Accurate estimation of burned areas can assist in decision-making after land fires and reduce the impact of land fires [1].

Remote sensing technology has become the primary tool for monitoring, analyzing, and recovering burned areas on a wide (global) or narrow (regional) scale. The agency provides accurate, fast results and diagnoses burned areas for postfire mitigation [3–5]. Satellite data play a significant role supporting knowledge about forest fires [6]. The imagery multispectral instrument (MSI) from the Sentinel-2 satellite can provide medium and high (10–20 m) spatial resolution information, which can help in fire monitoring [7, 8]. Multispectral sensors provide different wavelength spectral information, such as near-infrared (NIR) and short-wave infrared, (which) have the highest difference in values between burned and unburned areas [9, 10]. Several studies using the Sentinel-2 spectral indexes resulted in a high correlation between the Sentinel-2 data and the actual burned area validated through field measurements [10–13]. Considering several studies, Sentinel-2 has a higher statistical correlation value and higher classification accuracy than the Landsat 8 OLI imagery [13–15].

Identifying burned areas can be carried out by various methods/indexes, including Normalized Burn Ratio (NBR), Normalized Burn Ratio 2 (NBR2), Mid Infrared Burned Index (MIRBI), and Burned Area Index Sentinel 2 (BAIS2). Each index has advantages in mapping burned areas; the

MIRBI separability index distinguishes burned areas from open land. The NBR index differentiates burned areas with vegetation and built-up land, while the NBR2 index is ideal for determining smoky burned areas with built-up vegetation land [16]. This study's selection of the indexes refers to the land cover characteristics dominated by built-up vegetation. Hence, the NBR and RBR indices were adopted for burned area mapping.

The index commonly used to assess the burned area is the differenced normalized burn ratio (dNBR) using NIR and SWIR spectral band [10]. This spectral index is preferably used because it is less sensitive to atmospheric effects and can accurately measure the affected vegetation and reduce canopy humidity (decreased NIR value and increased postfire SWIR value) [17, 18]. The higher the reflectance value difference between the NIR and SWIR values, the more severe the burned area. In addition, the dNBR index can provide information about vegetation regeneration. Vegetation that begins to grow in a burned area has chlorophyll, reflecting a stronger signal in the NIR spectral [19, 20]. In addition to detecting burned areas and their severity, the Sentinel-2 satellite through the Copernicus program is currently the primary source of information on forest fires in Europe. In particular, the European Forest Fire Information Service (EFFIS), a database of meteorological and satellite mapping systems developed by the Joint Research Center (JRC) and the Emergency Mapping Service (EMS), with worldwide coverage, handles a wide variety of emergencies and disasters [21–25].

The dNBR application requires satellite imagery before and after the fire [26]. The before and after images of forest and land fires can be used for data from hotspot point analysis. Hotspots only indicate a fire's potential, so it is not fire. In other words, a burned area shows an actual fire, while a hotspot represents a potential fire [27]. The resulting classification is tested for a confusion matrix to know the accuracy of the dNBR processing results.

RBR is an alternative to dNBR, and RdNBRavoids some of the mathematical difficulties associated with the RdNBR equation. RBR is a relative version of dNBR or divided dNBR with a simple adjustment to the prefire NBR. Adding a denominator of 1.001 ensures that the denominator will never be zero to prevent the equation from reaching infinity and failing [28].

South Kalimantan is one of the wetland areas in Indonesia that always experiences land fires yearly. The burned areas in South Kalimantan have increased every year based on https://sipongi.menlhk.go.id. In 2018, land fires covered 9,8637.99 ha of land, while in 2019, it was 137,848.00 ha. The most vulnerable area to land fires in South Kalimantan is Banjarbaru. Banjarbaru's vulnerability to land fires is closely related to peatlands, overgrown shrubs, and less productive land [29].

Sentinel-2 imagery helps to monitor land fires, including wetland areas in South Kalimantan, especially in Banjarbaru. Increasingly widespread fires indicate ineffective ways of handling land fires. Sentinel-2 imagery using dNBR and RBR indexes can identify land fires in wetland areas. Sentinel-2 imagery can map the burned area and the severity of the fire [30]. Sentinel-2 imagery can be used to be effects of fires and allow for decision-making and land fires [31]. Through Sentinel-2 imagery, locations of severe damage can be identified, so handling can be carried out more appropriately by optimizing existing resources to prevent future fires [32]. This study aimed to analyze the dNBR and RBR fire index on Sentinel-2 imagery to monitor land fires in Banjarbaru in 2019.

2. Material and Methods

2.1. Study Sites. The study occurred in wetland areas, especially in Banjarbaru, South Kalimantan, Indonesia. Geographically, Banjarbaru is located between 3° 25′ 40″-3° 28′ 37″ S and 114° 41′ 22″–114° 54′ 25″ E (Figure 1). Banjarbaru experiences fire every year with an increasing number of hotspots. Based on the data from http://sipongi.menlhk.go.id., there were six hotspots in 2018 and 19 hotspots in 2019. The increase in hotspots has especially been found in peatlands [29].

2.2. Dataset. The burned areas have been mapped in South Kalimantan province using Landsat 8 imagery in 2019 [33]. Still, the spatial resolution needs to be increased to identify better and map burned areas, so this study uses Sentinel-2 imagery. The dataset consists of image data from Sentinel-2 and hotspot data. The Sentinel-2 imagery data were used before the fire recorded on 2019.06.06 and after the fire recorded on 2019.09.13. Table 1 presents the data before and after the fire based on data from Sentinel-2.

2.3. Calculation of NBR and dNBR. Sentinel-2 image data processing was carried out at this stage using SNAP software which can be accessed at Sentinel-2 Toolbox-STEP (esa.int). The difference in the resolution of each band in the image needed to be resampled with a spatial resolution of 10 m to composite images that were more diverse and used more complex bands. This NBR used the near-infrared (NIR) band eight and short-wave infrared (SWIR) band12 in Sentinel-2 imagery. dNBR processing was carried out on the two NBR images based on the prefire and postfire equations.

The equation used in the normalized burning ratio (NBR) method is as follows [34]:

$$\mathrm{NBR} = \frac{(\mathrm{NIR} - \mathrm{SWIR})}{(\mathrm{NIR} + \mathrm{SWIR})}, \tag{1}$$

where NBR is the normalized burning ratio, NIR is the near-infrared channel spectral value, and SWIR is the short-wave length infrared channel spectral value.

$$\mathrm{dNBR} = \mathrm{NBRprefire} - \mathrm{NBRpostfire}, \tag{2}$$

where dNBR is the differenced normalized burn ratio, NBR prefire is the NBR value before the fire, and NBR postfire is the NBR postfire value.

The purpose of calculating the image before (prefire) and after (postfire) in the dNBR calculation is to estimate the severity of the fire. We reduced the NBR values before and

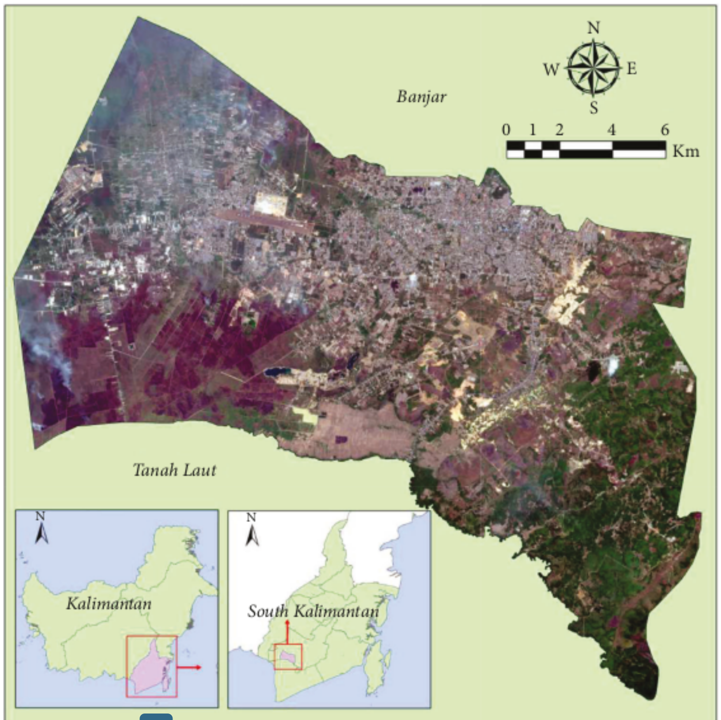


Figure 1: Map of the study area site in Banjarbaru.

Table 1: The description of the dataset.

Acquisition time	Satellite	Sources	Condition
2019.06.06	Sentinel-2	USGS	Prefire
2019.09.13	Sentinel-2	USGS	Postfire

after burning to reduce errors between areas highlighted only by NBR due to vacant land. We measured changes before and after roasting for a higher confidence level of burned areas. A high NBR value generally indicates good vegetation, while a low NBR value indicates vacant land and recently burned sites [35, 36].

2.3.1. Calculation of RBR (Relativized Burn Ratio). Relativized burn ratio (RBR) is an index that detects burned areas. The concept is similar to RdNBR [28]. The RBR equation is shown in equation [28], which isas follows:

$$\mathrm{RBR} = \frac{\mathrm{dNBR}}{(\mathrm{NBRprefire} + 1.001)}, \quad (3)$$

where RBR is the relativized burn ratio, dNBR is the differenced normalized burn ratio, NBR prefire is the NBR value before the fire, and 1.001 is the constant value.

2.4. Classification of Value Ranges. They are classifying the ranges of value to determine the severity of the burned area based on case studies' reference. RBR is a relative version of dNBR [28, 34], so we used fire severity classification values based on dNBR to classify RBR. From this stage onwards, the dNBR and RBR group values are classed in ArcMap software based on categories (Table 2).

Table 2: Severity by the dNBR value.

Severity by dNBR value	Fire severity
<−0.25	High postfire regrowth
−0.25 to −0.1	Low postfire regrowth
−0.1 to 0.1	Unburned
0.1 to 0.27	Low severity
0.27 to 0.44	Moderate-low severity
0.44 to 0.66	Moderate-high severity
>0.66	High severity

Source: (GSP, 2020).

At this stage, the class used is between the values of −0.1 to >0.66. This value maps unburned locations, low-severity fires, medium-low severity fires, medium-high severity fires, medium-high severity fires, and high-severity fires. Meanwhile, values of <−0.25 to −0.1 are not used in mapping because they require field data before and after fires to monitor vegetation growth before and after fires.

2.5. Validation of Burned Areas. Visual validation tests were performed by comparing RGB composite images to check the appearance before and after combustion with dNBR and RBR results. Visual validation aims to confirm the similarity of the resulting sightings and that fires do exist (truth), and the loss of plant vegetation in RGB composite sightings marks the presence of fires. dNBR and RBR on the visual similarity of objects are based on the conformity of classification indicators in representing their original appearance. Field validation is carried out by comparing the dNBR and RBR map values with field conditions.

Analysis of the accuracy test in this study was carried out using a confusion/error matrix. In measuring performance using a confusion matrix, 4 (four) terms represent the results of the classification process. The four terms are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The True Negative (TN) value is the correctly detected negative data, while the False Positive (FP) is the negative data detected as positive. Meanwhile, True Positive (TP) is positive data detected correctly, and False Negative (FN) is positive data seen as negative data.

Based on True Negative (TN), False Positive (FP), False Negative (FN), and True Positive (TP) values, accuracy, precision, and recall values can be obtained. The accuracy value describes how accurately the system can classify the data correctly. The accuracy value compares the information that is typed correctly and accurate data. The accuracy value can be obtained by Equation (4). The precision value describes the number of positive data categories classified correctly divided by the total data classified as positive. Precision can be obtained by Equation (5). Meanwhile, recall explains how the system correctly classified the percent of positive category data. The recall value is obtained by Equation (6).

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%, \quad (4)$$

$$\text{precision} = \frac{TP}{FP + TP} \times 100\%, \quad (5)$$

$$\text{recall} = \frac{TP}{FN + TP} \times 100\%. \quad (6)$$

This study used a confusion matrix calculator from https://www.marcovanetti.com/pages/cfmatrix/(Landis & Koch, 1977).

3. Result and Discussion

3.1. dNBR and RBR Spectral Transformation Capability for Mapping Burned Areas. Data on burned areas were obtained from the results of the RBR classifications applied to Sentinel-2 imagery on September 13, 2019 (postfire) and June 6, 2019 (prefire). The recording data were selected based on the results of the worst-case analysis, image availability, and freedom from image interference or noise caused by cloud cover in the Banjarbaru study area. The dNBR and RBR values indicated that the high value (>0.1) means that the area would be highlighted as experiencing a loss of vegetation or a burned area (Figure 2). This area has a shallow-medium density vegetation cover (such as shrubs, plantations, and open fields) (Figure 3).

The value of the burned area in Banjarbaru in 2019 based on the dNBR and RBR transformation was between 0.1 (low fire) to 1.4 (high fire). The center of forest and land fires in Banjarbaru in 2019 was the western region, Liang Anggang district, and Landasan Ulin district, marked by a dark pink-red hue. The pink color represents a low fire rate, while the dark red represents a high fire rate. Peatlands are dark red areas with high severity peatlands; peatlands always experience fires every dry season [29, 33, 37].

3.2. dNBR and RBR Burned Area Analysis in Banjarbaru. Data on the burned areas came from RBR and dNBR using the extract by mask on ArcMap 10.3. The burned areas were classified into five classes: unburned, low severity, moderate-low severity, moderate-high severity, and high severity with equal interval distribution, i.e., evenly dividing the resulting range of value of the burned areas.

dNBR classification resulted in a nonburned area of 30,315.15 ha and a high-severity burned area of 185 ha. RBR showed a nonburned size of 30,327.90 ha and a moderate-low severity burned area of 2.48 ha. The severity classification of the regions burned based on the dNBR and RBR transformation is presented in Table 3.

The burned area of moderate-high severity occurred in the peatland area (Table 3). This area is a peat area with land cover in the form of secondary forests and shrubs converted to agricultural areas or unmanaged shrubs. Conversion of land from secondary forest areas or shrubs through burning to become agricultural land has caused these areas to have moderate-high severity fires. Unmanaged and abandoned land with thick shrubs can burn during the dry season [38].

Comparisons were made between the vegetation density index image processing with the dNBR and RBR index images. Based on the comparison, it can be seen that the burned area is more concentrated around Liang Anggang district or the southwest of Banjarbaru. The concentration of burned areas in this area and the shrub area were converted for plantations. The results of field survey observations on converting land into oil palm plantations were obtained. In addition to converting land for plantations, the southwestern part of Banjarbaru is also used for housing development.

3.3. Burned Area Validation in Banjarbaru Area. Validation was carried out based on the similarity of the reference object with dNBR and RBR transformation maps. The proof showed a high level of confidence visually, and the RGB composite recorded on September 13, 2019 revealed many similarities with dNBR and RBR transformations maps on nonburnt objects (built-up land, water bodies, and nonvegetation) and burned things (loss of vegetation). The visual validation of the Banjarbaru burned areas based on the dNBR and RBR values are presented in Figure 4.

The survey was conducted at an affordable sample point for field validation tests. Table 4 shows similarities between visual and field observations in burned and unburned areas. Field validation of burned areas revealed regrowth after burning on the date of image recording, September 13, 2019

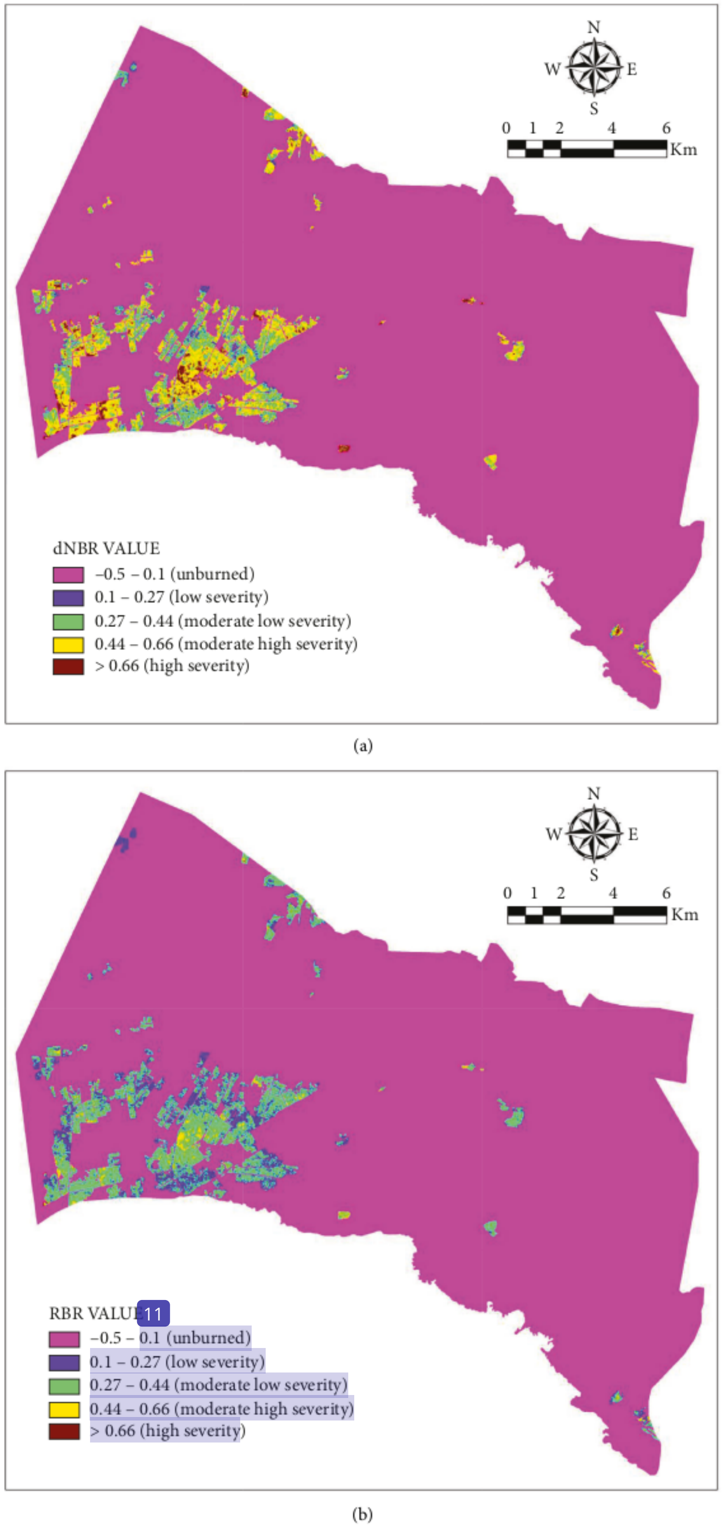


Figure 2: Burned area based on dNBR and RBR values in Banjarbaru.

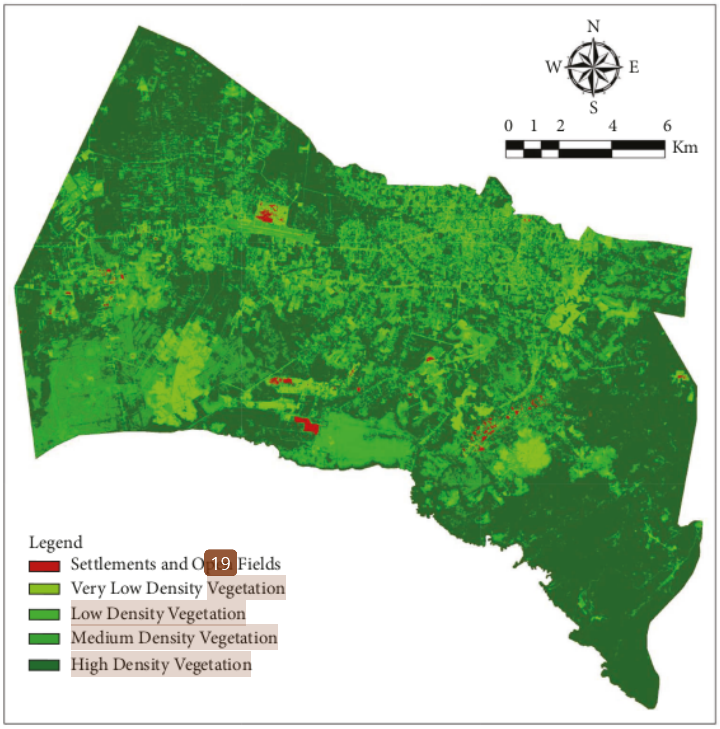


FIGURE 3: Map of vegetation density in Banjarbaru (2019).

(postfire). The field survey was conducted on May 20, 2021, 612 days after the fire. Evidence of charred remnants can be seen in Table 4.

The field observations indicate that the dNBR and RBR indices are valid. The burned area based on the dNBR and RBR indexes results also shows the burnt area in the field. Some rooms have shown that shrubs have started to grow on the burned area so that the burned area is covered, while the burned trees take a long time to grow back so that the burn marks are more clearly visible.

3.4. Analysis of dNBR and RBR Accuracy in Banjarbaru Area. Analysis of the fire severity on dNBR and RBR maps was crucial to reveal spectral transformation suitable to the conditions of Banjarbaru, which experienced a loss of vegetation. The analysis helped show the most significant spectral change and the accuracy values of dNBR and RBR in representing the burned and nonburned areas.

The overall accuracy of the classification results between the Sentinel-2 image composite with dNBR based on visual interpretations, with objects in burned and nonburned areas, was 91.5%. Overall accuracy exceeding 80% indicates very high accuracy. The burned area within the NBR index can distinguish between regions burned with vegetation and built-up land. The dNBR classification accuracy test results on burned areas are shown in Table 5.

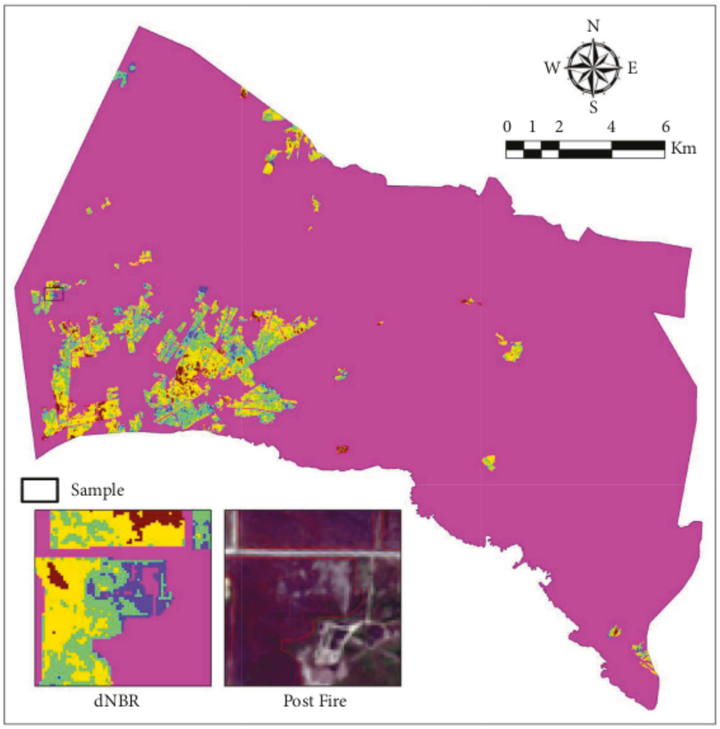
Table 5 confirms a sample of low severity as seen from the user accuracy, producer accuracy, and dNBR. Commission errors were found in the standard severity classes, around 43 points for the unburned class, 1 point for the low severity class, 59 points for the moderate-low severity class, and 1 point for the moderate-high severity class. The probability of additional classes in the low-severity class was about 77.33%. The high severity class had the highest level of user accuracy, with 99.49%, and the class that showed the lowest classification errors. Unburned classes were the lowest class in classification errors considering user accuracy (78.50%), and omission errors were found in the standard severity classes at around 43 points. Table 5 shows that overall accuracy is 91.5%, and kappa accuracy is 89.58%, and these values were used for the image accuracy level.

The overall RBR accuracy using Sentinel-2 was 92.9%, indicating very high accuracy. The burned area within the RBR index can distinguish between regions burned with vegetation and built-up land. The RBR classification accuracy test results on burned areas are shown in Table 6.

Table 6 confirms a sample of low severity as seen from the user accuracy, producer accuracy, and dNBR. Producer accuracy is most inadequate among other classes because other classes go into pixel classes with low severity. Commission errors were found in the standard severity class of about 2 unburned classes, 2 low-severity classes, 3 medium-low severity classes, and 4 medium-high severity classes. Based on the results of calculating the accuracy of RBR using a confusion matrix online calculator, it can be known that the accuracy of RBR in Banjarbaru is 92.9%, and the Kappa

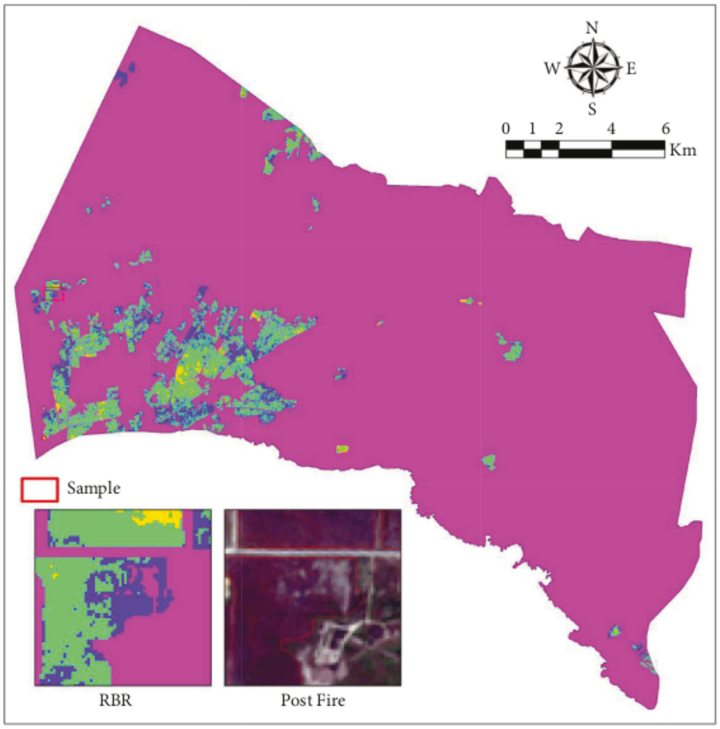
Table 3: Severity classification of the burned areas based on the dNBR and RBR transformation in Banjarbaru.

No.	Value	Classification	Area (dNBR) (ha)	Area (RBR) (ha)
1	−0.5–0.1	Unburned	30,315.15	30,327.90
2	0.1–0.27	Low severity	128.96	630.13
3	0.27–0.44	Moderate-low severity	961.34	1844.613
4	0.44–0.66	Moderate-high severity	1333.36	118.687
5	>0.66	High severity	185	2.48
Total area	32,923.81	32,923.81		



(a)

Figure 4: Continued.



(b)

FIGURE 4: Visual validation of burned areas in Banjarbaru.

coefficient is 0.911. Then, it can be understood that the accuracy of RBR in Banjarbaru is 92.9%, and the Kappa coefficient is 0.911.

Based on Tables 5 and 6, it can be seen that class 1 is the class that causes much bias in the field. This bias is seen particularly for dNBR and slightly in RBR-derived images. This bias is starting to be seen because several areas initially experienced fires but have already experienced vegetation growth. This area, in particular, is an area that is dominated by shrubs, so it is rapidly growing. This scrub area is also interspersed with several collections of *Galam* vegetation *(Melaleuca leucadendron)* so that the burn marks remain visible.

Overall, the analysis of forest and land fires in Banjarbaru resulted in a higher accuracy of RBR in measuring the severity of fires compared to dNBR, with an accuracy difference of 1.4%. This result supports the research conducted by [28], showing that the RBR index has a good performance in revealing the severity of fires validated through field measurements. RBR is a helpful metric across various geographies and ecosystems in our study and the wetland areas [39].

RBR is a relative version of dNBR, designed to detect changes even in prefire vegetation covers. The main strength of the RBR equation is that it avoids some of the mathematical difficulties associated with the dNBR equation [28]. The RBR equation (1) does not fail (it is infinite) for any prefire NBR value (including zero), (2) does not produce very high or low values as the prefire NBR approaches zero, and (3) retains the prefire NBR signs, thus avoiding the potential for arbitrary bias in retrieving absolute values. In addition, the decrease in the RBR threshold variability among fires indicates that the RBR threshold is more "stable" than the RdNBR threshold and, thus, more transferable between fires and ecoregions [40,41].

Regions of high severity are marked in dark red (Figure 3). This area is generally peatlands with shrubs. Peatlands in the study area always experience fires every dry season. In addition, many peatlands have been cultivated and drained, so they are always dry in the dry season [29]. Both indices can be used for burned area mapping in wetland areas, with an accuracy rate of >80%. Both indices can accelerate the handling and mitigation of land fires, especially in areas with high fire severity, especially peatlands. Using the dNBR and RBR indexes on Sentinel-2 imagery, burned area mapping can help handle land fires in wetland areas.

Sentinel-2 is part of a plan to publicize already available big spatial data in disaster mapping in the wetland area. Sentinel-2 spatial capabilities give it an edge in the ability for land fire mapping. The spatial resolution of Sentinel-2, which reaches 10 m, coupled with the results of this study, is expected to be a medium in the event of land and residential

Table 4: Field validation of burned areas in Banjarbaru.

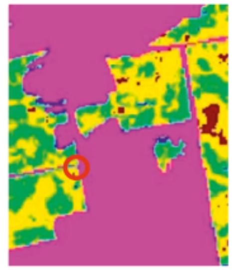
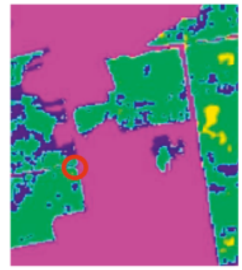
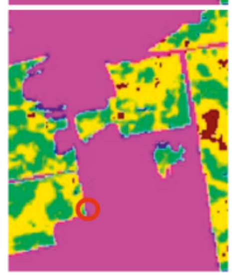
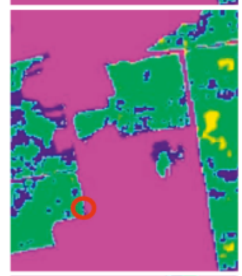
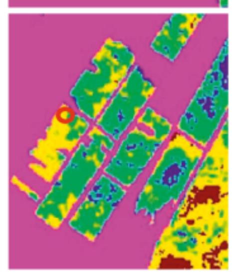
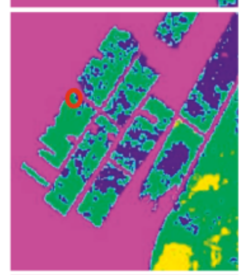
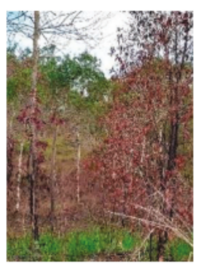
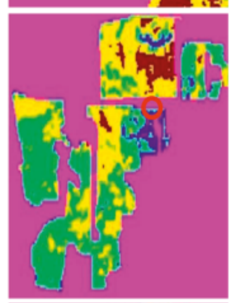
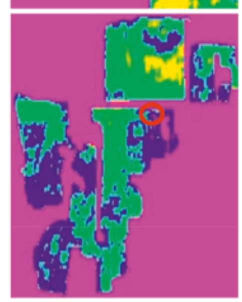
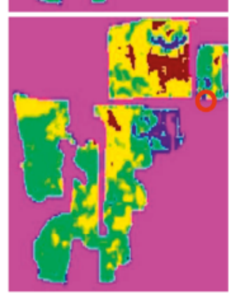
No	Coordinates X	Coordinates Y	Location	dNBR map	RBR map
1.	144°42.450′E (144.707593)	03°28.848′S (−3.480760)			
2.	144°43.508′E (144.725218)	03°28.783′S (−3.479682)			
3.	144°41.237′E (144.687369)	03°27.788′S (−3.463092)			
4.	144°41.334′E (144.689158)	03°27.796′S (−3.463232)			
5.	144°42.450′E (144.707593)	03°28.848′S (−3.480760)			

Table 5: dNBR confusion matrix in Banjarbaru.

	Classification results					
	1	2	3	4	5	User accuracy (%)
1	157	43	0	0	0	78.50
2	4	185	10	1	0	92.50
3	0	9	179	12	0	89.50
4	1	1	1	196	1	98.00
5	0	0	0	2	198	99.00
Truth overall	162	238	190	211	199	
Producer accuracy (recall)	96.91%	77.73%	94.21%	92.89%	99.49%	

Table 6: RBR confusion matrix in Banjarbaru.

	Classification result					
	1	2	3	4	5	User accuracy (%)
1	178	14	6	2	0	89
2	2	174	22	2	0	87
3	3	4	181	12	0	90.5
4	0	0	4	196	0	98
5	0	0	0	0	200	100
Truth overall	183	192	213	212	200	89
Producer accuracy (recall)	97.26%	90.62%	84.97%	92.45%	100%	

fires. The ten days of the temporal resolution of Sentinel can be maximized in future research for land fire mapping and modeling. This can be an instrument in disaster mitigation, especially for wetland land fires, and are detrimental to many parties.

Applying the dNBR and RBR methods in this study continues previous research [33]. The indicated index obtained a threshold for peat fires in Banjarbaru and South Kalimantan. The values obtained can then be used to develop a land fire model. This model is expected to find out the pattern of fires and, at a later stage, to prevent fires in other areas.

4. Conclusions

The dNBR classification on fire severity in Banjarbaru in 2019 showed values from 0.1 (low fire) to 1.41642 (high fire). The dNBR classification class resulted in an unburned area of 30,315.15 ha, an intense fire of 128.96 ha, a moderate-low fire of 961.34 ha, a moderate-high fire of 1333.36 ha, and a high fire of 185 ha. The classification accuracy results of the dNBR transformation minus burned areas were delineated from visual interpretation. Sentinel-2 RGB composite images after burning showed an overall accuracy of about 91.5% and a kappa accuracy of 0.89 (the accuracy probability is very good or almost perfect). The RBR classification on fire severity highlighted an unburned area of 30,327.9 ha, a low fire of 630.13 ha, a medium-low fire of 1844.61 ha, a medium-high fire of 118.69, and a high fire of 2.48 ha. The classification accuracy results of the RBR transformation showed an overall accuracy of about 92.9% and a kappa accuracy of about 0.91 or 91% (the accuracy probability is excellent). Both indices have perfect accuracy in burned area mapping wetland areas that experience land fires. We recommend further research identifying other indexes to map land fires' burned areas in wetland areas.

Sentinel-2, which includes images with medium spatial resolution, is a widely used image in this field. Maximizing the use and function of Sentinel-2 can assist the researcher in producing further research, especially related to the mapping and modeling of burned land in Kalimantan. The application of various fire indices and the resulting variations in accuracy is expected to be a model in helping to overcome the problem of land fires in South Kalimantan, which is still a national and international issue. Appropriate modeling is a means of input for local and central governments in conducting national fire disaster mitigation management.

Data Availability

The data supporting this article are from datasets that have been cited.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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