Forest fires and carbon emission release in semi-arid regions of Indonesia: the evidence from medium resolution of satellite imagery

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Abstract. Forest fires are one of the causes of forest degradation and deforestation in Indonesia. Tropical savanna forests are one of the forest ecosystems found in the Indonesian region with a semi-arid climate type prone to drought and fire. Forest fires contribute to the release of greenhouse gas emissions into the atmosphere. The calculation method to estimate the burnt area is still an obstacle in calculating greenhouse gas emissions due to forest fires. This research aims to assess the burnt area in tropical savanna forest cover type using medium resolution satellite imagery data by utilizing the Normalized Burn Ratio index in four villages in East Sumba Regency and estimating greenhouse gas emissions these activities. The results showed that the NBR method does not produce an estimate of the burned area with a fair degree of accuracy because the characteristic of channel 7 (SWIR) is sensitive to vegetation moisture content. The savanna forest cover type is the type of land cover identified as the most dominant burned area. It produces the highest greenhouse gas emissions compared to other land cover types.

1. Introduction

Tropical savanna forest is a unique forest ecosystem type mainly found in semi-arid regions with less rainfall and warm temperatures. Tropical savanna forest covers about 15% of Earth’s surface, and it is characterized by the presence of grasslands, shrubs, and trees which create complex and dynamic landscapes altogether [1]. The savannah ecosystem is a climax ecosystem due to the influence of fire (fire climax vegetation). The effect of fire, through forest fires, is a controlling factor for the development of the savannah ecosystem. Fire plays an essential role in forming crops that grow in dry climates with high evapotranspiration rates [2].

Tropical savanna forest biomass plays a vital role in the global carbon cycle, in which about 30% of Net Primary Production (NPP) is produced by tropical savanna forest. However, the vulnerability of forest fires in tropical savanna forest potentially to release large amounts of carbon into the atmosphere, which is about 20% of the biomass produced by tropical savanna forest [3]. Thus, carbon stock in tropical savanna forest is less than in other ecosystems, such as tropical rainforests [4].

Forest fires occurrences can be identified regarding satellite imagery data's spectral reflectance characteristics with low, medium, and high spatial resolution [5-7]. The approach method to determine the forest fires occurrence and the estimation of the burnt area can be done by utilizing a combination of brightness values from various bands, such as the red band, near-infrared (NIR) band, and shortwave infrared (SWIR) band [8]. The Normalized Burn Ratio (NBR) is one of the spectral indexes that has been widely used to identify the forest fires occurrence utilizing the NIR and SWIR band.
Tropical savannah forest, such as found in East Sumba Regency, East Nusa Tenggara Province, is the dominant land cover type in Indonesia's semi-arid region. The savannah ecosystem is vulnerable to drought and forest fires, potentially emitting greenhouse gases (GHG) emissions. Therefore, this paper aims to identify the burnt area in tropical savannah forest based on the NBR spectral index from the medium resolution of satellite imagery data, such as LANDSAT-8 OLI, and the possible amount of GHG emissions released.

2. Research method
LANDSAT-8 OLI orthorectified surface reflectance of satellite imagery data was used to identify the forest fires occurrences in Ndapayami and Mondu Village, Kanatang Subdistrict, and Pambotanjara and Mbatakapi Village, Waingapu City District, East Sumba Regency, East Nusa Tenggara Province. SWIR band sensitive to vegetation burn patches [9] and the NIR band sensitive to variations in greenness or vegetation health in LANDSAT-8 OLI imagery data [10-11]. Thus they were used to calculate the Normalized Burn Ratio index to identify forest fires occurrence and its severity. LANDSAT-8 OLI imagery data was acquired for the study area, then mosaicking and atmospheric correction were made. The imagery data's acquisition dates are determined based on the pre-fire and post-fire dates from hotspot data (Table 1). The digital number in LANDSAT-8 OLI imagery data is converted into the peak atmospheric spectral reflection value ($\rho_\lambda$) to calculate the NBR index using the following equation:

$$\rho_\lambda = M_\rho \times Q_{cal} \times A_\rho$$  

(1)

where:

$\rho_\lambda$ = spectral values (W/(m$^2$.sr.μm)),

$M_\rho$ = the spectral reflection multiplier scale factor for the each band (W/(m$^2$.sr.μm)),

$Q_{cal}$ = pixel value from digital number (DN), and

$A_\rho$ = the reflection enhancer scale factor for the each band (W/(m$^2$.sr.μm)).

| Year | Fire periods | Satellite imageries acquisition dates |
|------|--------------|--------------------------------------|
|      |              | Path 113 row 67                       |
| 2016 | Before       | 03/09/2016, 02/08/2016                |
|      | After        | 22/11/2016, 08/12/2016                |
| 2017 | Before       | 15/05/2017, 01/05/2017                |
|      | After        | 09/11/2017, 25/11/2017                |
| 2018 | Before       | 08/08/2018, 23/07/2018                |
|      | After        | 27/10/2018, 28/11/2018, 14/12/2018    |
| 2019 | Before       | 26/07/2018, 27/08/2019, 11/08/2019    |
|      | After        | 01/12/2019, 17/12/2019               |

All imageries data is used to determine the Normalized Burn Ratio, both before and after fire occurrences. Thus the NBR$$_{pre}$ (NBR before fire occurrences) and the NBR$$_{post}$ (NBR after fire occurrences) images are obtained. NIR band (band 5) and SWIR2 band (band 7) were extracted from LANDSAT-8 OLI imagery data to determine NBR values using the following equation:

$$NBR = \frac{B_5 - B_7}{B_5 + B_7}$$  

(2)

where:

NBR = Normalized Burn Ratio

$B_5$ = reflectance band 5 (NIR; 0.845 – 0.885μm)

$B_7$ = reflectance band 7 (SWIR; 2.100 – 2.300μm).

Normalized Burn Ratio (NBR) image data for pre- and post-fire in 2016 – 2019 would then be extracted based on the threshold value. A burnt area is defined by a pixel which meets two prerequisites of the burnt area pixel threshold:
Prerequisite 1: IF \( \text{NBRpost}_{ij} \leq \alpha \)
Prerequisite 2: IF \( \Delta \text{NBR}_{ij} \geq \beta \)

where \( \Delta \text{NBR}_{ij} = \text{NBRpre}_{ij} - \text{NBRpost}_{ij} \)

where:
\( \Delta \text{NBR}_{ij} \) = change in NBR value for certain pixels,
\( \text{NBRpost}_{ij} \) = NBR value for a particular pixel after fire occurrence,
\( \text{NBRpre}_{ij} \) = NBR value for a particular pixel before fire occurrence,
\( \alpha \) = threshold value for NBR after fire occurrence, and
\( \beta \) = threshold value for changes in NBR.

Statistically, the threshold value can be measured from the mean value (\( \mu \)) and standard deviation (\( \sigma \)) of the sample area representing the NBRpost and \( \Delta \text{NBR} \) images' burnt area. The threshold value chosen is the value of \( \mu \pm 2\sigma \) using the assumption of a normal distribution. Furthermore, based on these assumptions and criteria (\( \mu \pm 2\sigma \)), the \( \alpha \) value is obtained from the mean value plus two times of standard deviation of the burnt area sample in the NBRpost image. The \( \beta \) value is obtained from the mean value minus two times of standard deviations from the burnt area sample in the \( \Delta \text{NBR} \) image.

The accuracy test for the classification of burnt and not burnt areas is done using an error matrix (producer's accuracy, user accuracy, and overall accuracy). The error matrix is used to calculate the omission and commission error (Table 2). Omission error is the total area that is not identified as a burnt area based on the model results but is identified as a burnt area in reference or observation data. Commission error is an area that is recognized as a burnt area in the model results but is identified as a not burnt area in reference or observation data. Valid data is the area identified as the burnt area in the model results and reference data. It is used to calculate the producer's accuracy, user's accuracy, and overall accuracy between the model's results and reference data [12].

| Model data       | Reference data |
|------------------|---------------|
| Burnt (ha)       | Burnt (ha)    |
| Unburnt (ha)     | Unburnt (ha)  |
| Valid data (X)   | Valid data (X) |
| Commission error (Y) | Omission error (Z) |
| User's accuracy (%) | \( [X/(X + Y)] \times 100\% \) |
| Producer's accuracy (%) | \( [X/(X + Z)] \times 100\% \) |
| Overall accuracy (%) | \( [X/(X + Y + Z)] \times 100\% \) |

The estimation of GHG emissions is estimated from data processing on the burnt area and then calculated using an equation developed from IPCC 2006. The method for estimating GHG emissions due to forest fires is presented in Equation 3. The estimated GHG emissions due to forest fires are calculated for each type of gas (CO2 and non-CO2); thus, an estimate of CO2-eq emissions due to forest fires will be obtained.

\[
L_{\text{fire}} = A \times M_B \times C_f \times G_{ef} \times 10^{-3}
\]  

(3)

where:
\( L_{\text{fire}} \) = the amount of GHG emissions due to forest fires, in tonnes for each gas, i.e., CH4, N2O, etc.,
\( A \) = burnt area, in hectares,
\( M_B \) = load of burned fuel, in tonnes ha\(^{-1}\); includes biomass, litter, and deadwood,
\( C_f \) = combustion factor; no units, and
\( G_{ef} \) = emission factor, in g kg\(^{-1}\) of burned dry fuel.
GHG emissions from forest and land fires are reported in total CH4, CO, N2O, and NOx. Methane (CH4) and N2O emissions are converted to CO2-eq emissions using global warming potential, with a value of 28 and 265, respectively [13]. Since CO and NOx are secondary GHGs, they are not converted to CO2-eq. Therefore, total GHG emissions from forest and land fires will be produced in tonnes CO2-eq.

3. Result and discussion

3.1. Main indicators of savannah forest fires

The distribution pattern of monthly hotspots in the study area fluctuated during 2016 - 2019 and formed a peak in the fire period (Figure 1a). The number of hotspots with a confidence level greater than 80% in the study area during 2016 - 2019, respectively, i.e., 8, 15, 14, and 7. The increase in hotspots mainly occurred in August, then decreased until October. Based on the monthly hotspot distribution pattern, it can be seen that the peak period of the savanna forest fires in the study area in 2016 - 2019 occurred around August.

The peak period of savanna forest fires in the study area is related to the dry season’s peak in the study area. Based on the precipitation pattern in Figure 1b, the study area has a monsoonal precipitation pattern, which has one dry season peak, i.e., in June - August [14]. Rainfall is a climatic factor that indirectly affects forest and land fires because rainfall can affect the fuel’s humidity conditions. The level of rainfall distribution affects the number of fire events that can be identified through hotspots. Based on Figure 1b, the emergence of hotspots in the study area generally occurs during the dry season and transition (dry to wet), i.e., July - October.

![Figure 1](image1.png)

*Figure 1. (a) Number of hotspots (confidence level ≥ 80%) and (b) Distribution of monthly precipitation and number of hotspots (confidence level ≥ 80%) in the study area in 2016 – 2019*

Based on historical data for hotspots for 2016 - 2019 with a confidence level greater than 80%, it can be seen that the distribution of hotspots in the study area looks clustered (Figure 2). Mondu and Ndapayami villages are the two villages with the most distribution of hotspots during 2016 - 2019, with 14 points each. The hotspots are generally located around the border area between Mondu village and its neighboring villages and Ndapayami village and its neighboring villages.
3.2. The threshold of the burnt area and identification of the burnt area

The determination of the threshold value for identifying burnt and unburned areas in tropical savanna forests in the study area was carried out using training sample burnt area data based on semi-automatic approaches using RGB composite channel 654. LANDSAT-8 OLI satellite imagery in the pre- and post-fire periods in each year is used to detect burned areas. Visual detection of burnt areas is only carried out in places with hotspots, smoke, and pixels indicated as fire or flames. The burnt area in the LANDSAT-8 OLI image is visually shown by (1) reddish-brown color and darker than the surrounding area, (2) the pattern is irregular, (3) there is depression as a form of fire propagation, and (4) the texture is smooth. The delineation of burned areas visually is used to create training sample data for burnt areas using the NBR method. Based on the mean value and standard deviation of each of the training sample data, it can be obtained the reflectance value after the fire ($\alpha$) and change difference ($\beta$) for each year, then used as a prerequisite for determining the threshold value for identification of burned area (Table 3).

| Year | The reflectance value after fire occurrence ($\alpha$) | Change difference ($\beta$) |
|------|---------------------------------|-----------------------------|
| 2016 | 0                               | 0                           |
| 2017 | 0.04                            | 0.33                        |
| 2018 | 0.27                            | -0.19                       |
| 2019 | 0.13                            | 0.02                        |
| Average | 0.11                        | 0.04                        |

Estimating the burned area using the NBR index based on the predetermined threshold values shows that burned area is distributed in each village each year (Figure 3). Mondu and Ndapayami villages are the two villages that tend to have the highest burned areas each year. The burned areas in 2016 - 2019, based on the NBR index, were 7240.93 ha, 15523.14 ha, 10945.05 ha, and 8569.60 ha, respectively. Land cover types in the form of savanna forest and bush/shrubs are the two types of land cover identified as the most dominant burned areas in 2016-2019 in the study area (Table 4). However, a type of primary
dryland forest cover was identified as the area burned in 2017 - 2019 in the study area, even though it had a small burnt area.

Table 4. The total amount of burnt area for each land cover type based on the NBR method

| Land Cover Type       | Burnt Area (ha) | 2016 | 2017 | 2018 | 2019 |
|-----------------------|-----------------|------|------|------|------|
| Primary Dryland Foret |                 | 0    | 2.37 | 6.92 | 1.45 |
| Settlement Area       |                 | 0.12 | 4.75 | 1.16 | 3.60 |
| Savannah Forest       |                 | 7214.69 | 15458.34 | 10894.52 | 8515.45 |
| Bush/Shrub            |                 | 22.15 | 53.28 | 37.62 | 45.48 |
| Barren Land           |                 | 0.12 | 4.40 | 4.83 | 3.61 |

3.3. Accuracy test
The accuracy level calculation is carried out, by comparison, using reference data, i.e., the burned area data from the Ministry of Environment and Forestry in Indonesia. The accuracy test was carried out by overlaying the NBR model's burned area with the burned area data from the reference map. The calculation is made based on the number of polygons of the NBR model's burned area, including or exclude the burned area according to the reference map.
The accuracy test shows that the estimated burnt area based on the NBR model has a low overall accuracy (less than 50%) (Table 5). The estimated burned area's accuracy rate in 2016 - 2019 is 0%, 50.62%, 13.46%, and 13.56%, respectively. This level of accuracy is relatively low because there are omission errors and commission errors, i.e., the area that is not burned but detected as burned areas and the area that is burning but are not detected as burned areas. It is due to band 7 (SWIR) sensitivity in the LANDSAT-8 OLI satellite image to the water content of vegetation [15]. Thus, identifying burned areas using NBR shows that almost all of the tropical savanna forest during the dry season (fire period) is a burned area because it has a lower water content than during the rainy season.

| Accuracy Parameter          | 2016      | 2017      | 2018      | 2019      |
|----------------------------|-----------|-----------|-----------|-----------|
| Valid data (ha)             | 0         | 8816.25   | 2613.26   | 3591.03   |
| Omission error (ha)         | 0         | 1894.51   | 8464.92   | 17919.92  |
| Commission error (ha)       | 807.12    | 6706.89   | 8331.79   | 4978.57   |
| User’s accuracy (%)         | 0         | 56.79     | 23.88     | 16.69     |
| Producer’s accuracy (%)     | -         | 82.31     | 23.59     | 41.90     |
| Overall accuracy (%)        | 0         | 50.62     | 13.46     | 13.56     |

The LANDSAT-8 OLI satellite imagery has a spatial resolution of 30 meters, which means that the detectable burnt area is at least 0.09 hectares. The LANDSAT-8 OLI satellite imagery can detect the burnt area of fewer than 25 hectares, but optical imagery has a weakness, i.e., cloud cover. The presence of cloud cover on the LANDSAT-8 OLI satellite imagery also affects the resulting NBR index value. The total amount of burned area based on the valid data from the accuracy test is given in Table 6.

| Land Cover Type     | Burnt Area (ha) |
|---------------------|-----------------|
|                     | 2016  | 2017  | 2018  | 2019  |
| Savannah Forest     | 0     | 1498.02 | 654.9 | 1699.79 |
| Bush/Shrub          | 0     | 0     | 6.93  | 0     |
| Total CO2-eq        | 0     | 1498.02 | 661.83 | 1699.79 |

3.4. Greenhouse gases emissions released from savanna forest fires
The calculation of the estimated greenhouse gas emissions resulting from tropical savanna forest fires in the study area was carried out using the burned area data included in the valid data category from the accuracy-test result. Estimating greenhouse gas emissions from tropical savanna forest fires in the study area was calculated for two land cover types identified as burned areas from the valid data, i.e., savanna forest and bush/shrub (Table 6). Savanna forests released the highest carbon emissions in 2016 - 2019 compared to bush/shrub. Due to the savanna forest cover type in the study area in 2016 - 2019 has the highest burned area, the loss of carbon stock due to forest fires is also more significant. Although bush/shrub has the highest amount of fuel mass and combustion factor value, bush/shrub's burned area is relatively low in the study area. Thus it emits the lower amount of greenhouse gas emissions from biomass burning. The highest emission of greenhouse gases occurred in 2019, namely $894 \pm 384.9$ tons CO2-eq, which is due to the area burned in 2019 was the highest during 2016 - 2019 in the study area.
4. Conclusion
The estimated area burnt in tropical savanna forests in Indonesia is still less known due to specific vegetation cover types in semi-arid regions and the absence of direct measurements in the field. One remote sensing technique to estimate the burnt area using medium resolution satellite imagery data can be done by utilizing the Normalized Burn Ratio (NBR) index. Many hotspots occur in the study area during the dry season (June - August), where the fire period peak occurs in August. The burned area's estimation results using the NBR index show that the area burned in 2019 was the highest burned area in which the land cover type that prone to fires was consecutively from the highest, i.e. savanna forest and bush/shrub. The accuracy-test results show that the NBR method does not predict the burnt area for tropical savanna forest cover very well because the characteristic of band 7 (SWIR) is sensitive to changes in vegetation water content. Estimating greenhouse gas emissions due to forest fires also shows a similar result: the savanna forest cover type releases the highest greenhouse gas emissions.

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