Deforestation detection using multitemporal satellite images

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Abstract. Indonesia a megadiverse country which has the largest area of forest with the richest biodiversity in the world. Unfortunately, the forest-loss in this country is quite big, especially in Kalimantan and Sumatera. Therefore, a robust method for deforestation method has to be developed to monitor deforestation to minimize the forest-loss in this country. In this paper, we proposed a method for deforestation detection called Multitemporal Deforestation Detection (MDD). The basic idea of this method is to utilize the difference of reflectance values on the target image and original image. Band selection was used to select bands in developing the algorithm. To improve the accuracy of the results, NDVI and dNBR were combined to the algorithm. As a result, the MDD can detect deforestation from forest to heterogeneous land cover such as open land, land clearing for plantation, urban, road and small road, and burnt area accurately. The advantage of the MDD is that it does not interfere cloud and cloud shadow on the original image. As it is an automatic algorithm, it can support in detecting deforestation for a big dataset.

1. Introduction
Sentinel-2 mission is a constellation with two twin satellites i.e., Sentinel-2A and Sentinel-2B. This constellation makes Sentinel-2 has a high revisit time (10 days at the equator with one satellite, and 5 days with 2 satellites under cloud-free conditions which results in 2-3 days at mid-latitudes). Based on this revisit time, it can be used to support monitoring of Earth's surface changes such as land use land cover change [1-4], forestry [5, 6], agriculture [7, 8], and time series analysis [9-11].

Indonesia is one of the countries which has a largest area of forest in the world. The biggest issue in this country related forest area is a forest loss. The two biggest loss of forest are in Kalimantan and Sumatera. Besides logging and commercial agriculture, another tool used in the deforestation process are fires [12]. To minimize deforestation issue, a robust method of deforestation needs to be developed to support monitoring deforestation in Indonesia. In decades, the deforestation methods have been developed such as [13-19]. Spatial-temporal scan statistics was used to detect deforestation in Brazilian Amazonia [19]. There are some deforestation detection system such as DETER-B - The New Amazon Near Real-Time Deforestation Detection System [17].
In this study, we proposed a method of deforestation detection for Sentinel-2 using multitemporal images called Multitemporal Deforestation Detection (MDD). This method will be evaluated for Sentinel-2 images by visual and statistical assessments. To assess the reliability of this method, we will use the MDD for Sentinel-2 images with a variety of forest changes such as forest to land clearing for plantation, forest to urban, forest to open land, forest to road, and burnt area.

2. Data and study area

2.1. Data

Sentinel-2 was launched on June 23, 2015, was designed with multispectral sensor for surveying with 13 bands in the visible, near infrared, and shortwave infrared part of the spectrum and the resolution is 10 to 60 m in the spectrum.

Table 1. Spectral bands of Sentinel-2

| Sentinel-2 Band (µm) | Resolution (m) |
|---------------------|----------------|
| Band 1 (0.433–0.453) | 60             |
| Band 2 (0.458–0.523) | 10             |
| Band 3 (0.543–0.578) | 10             |
| Band 4 (0.650–0.680) | 10             |
| Band 5 (0.698–0.713) | 20             |
| Band 6 (0.733–0.748) | 20             |
| Band 7 (0.765–0.785) | 20             |
| Band 8 (0.785–0.900) | 10             |
| Band 8A (0.855–0.875) | 20           |
| Band 9 (0.930–0.950) | 60             |
| Band 10 (1.365–1.385) | 60            |
| Band 11 (1.565–1.655) | 20            |
| Band 12 (2.100–2.280) | 20            |
2.2. Study area
In this study, some areas of deforestation are used to test the reliability of the proposed method, i.e., (1) a part of Kalimantan Timur Province (see figure 2(a), 2(b) and 2(c), and (2) a part of Kepulauan Riau Province (see figure 2(d)). In figure 2, it shows the target images which has deforestation area caused by various circumstance such as deforestation from forest to land clearing for plantation, forest to urban, forest to open land, forest to road, and forest to burnt area.

![Figure 2. The study areas. Red box points (a), (b), (c) and (d), and blue box points (e)](image)

3. Methods

3.1. Developing Multitemporal Deforestation Detection Algorithm
The basic idea of MDD is to use the difference of reflectance values of target image and original image to detect deforestation. Target image is an image which has deforestation pixels and original image is an image which has no change for forest pixels on the image. There are two main steps to develop the MDD algorithm: band selection and additional parameters. First, we select suitable bands for detecting deforestation. In this step, we take some pixels on the target image and original image, which represent deforestation such as forest to land clearing for plantation, forest to urban, forest to open land, forest to road, and forest to burnt area. Afterwards, we calculate the difference of reflectance values from them. After that, we select bands which have the bigger different values from the results. Moreover, we also select the threshold by conducting some observations.

Second, we add some parameters such as NDVI and NBR to increase the accuracies of the results. NDVI is used to minimise commission error usually caused land cover change and natural phenomena. On the other hand, difference NDVI (dNDVI) is used to detect deforestation caused forest fire as burnt area.

The followings are the bands selection process for detecting deforestation in a heterogeneous land cover. In those figures, original image and target image is Sentinel-2 image in 2018 and 2019, respectively. Figure 3 shows reflectance values of a pixel on forest on the original image to open land on the target image. We can see that the big difference of the reflectance between in SWIR band (bands 11 and 12), vegetation red edge (bands 5 and 7), and red band (band 4). We chose band 11 instead of band 12 as it has a bigger difference of reflectance value in almost of the scenarios. We also chose band 4 with the
same reason. In contrary, band 5 and band 7 were not selected as they were inconsistent in terms of the big different reflectance such as in figures 5, 6 and 7. Based on those figures, we select band 11 and band 4 in detecting deforestation. According to the band selection and observing thresholds, we found an optimal algorithm in detecting deforestation in a heterogeneous land cover by using red and SWIR band. However, if an unusual circumstance occurred such as cloud shadow on the original image, it will be identified as deforestation because the difference between forest pixels on target image and forest pixels with cloud shadow on original images are quite big. Cloud shadow makes the reflectance values of forest much lower. To minimize commission error caused this circumstance, we used Normalized Difference Vegetation Index (NDVI) on the original image. The following is the algorithm of MDD for land cover change (from forest to others).

\[ B4(TI) - B4(OI) > 200 \text{ and } B11(TI) - B11(OI) > 500 \text{ and } \left( \frac{(B8(OI) - B4(OI))}{(B8(OI) + B4(OI))} \right) > 0.5 \]  

\[ (1) \]

Where

- \( B4(TI) \)= Band 4 on target image
- \( B4(OI) \)= Band 4 on original image
- \( B8(OI) \)= Band 8 on original image
- \( B11(TI) \)= Band 11 on target image
- \( B11(OI) \)= Band 11 on original image

**Figure 3.** Reflectance values of a pixel on forest to open land.
Figure 4. Reflectance values of a pixel on forest to open land.

Figure 5. Reflectance values of a pixel on forest to land clearing for plantation (bright).

Figure 6. Reflectance values of a pixel on forest to land clearing for plantation (dark).
Figure 7. Reflectance values of a pixel on forest to small road.

Figure 8. Reflectance values of a pixel on forest to road.

Besides land cover change from forest to others, deforestation can be caused by fire forest. It provides a burnt area. Therefore, we will combine a burnt area detection algorithm to eq. 1 to detect deforestation. Normalized Burn Ratio (NBR) is an index which can be used to identify burned areas and estimate fire severity. We can see in figure 8 that healthy vegetation such as forest can be identified as a very high reflectance in the NIR. In contrary, it shows low reflectance in the SWIR. It can also be seen that in areas devastated by fire is the opposite, the burned areas demonstrate low reflectance in the NIR and high reflectance in the SWIR. figure 9 shows that the difference between the spectral responses of healthy vegetation and burnt areas reach their peak in the NIR and the SWIR. Thus, we can use this circumstance to detect deforestation caused forest fire. The difference between the spectral responses of healthy vegetation and burnt can be described as dNBR.
Figure 9. Comparison of healthy vegetation and burned areas in the spectral response. Source: U.S. Forest service.

Figures 7 and 8 show the reflectance value of a pixel on forest to burnt area. We selected and categorised burnt area visually into two classes: dark brown and light brown. In dark brown area of burnt, we can see clearly that the big difference of reflectance value between original image and target image are on bands vegetation red edge (bands 6 and 7), NIR (bands 8 and 8A), and SWIR (bands 11 and 12). Based on these figures, we used NIR and SWIR as bands for dNBR. In figures 10 and 11, we can see that bands 6 and 7 can be used to detect burnt area as well. We chose band 7 instead of band 6 as the difference of original image and target image is bigger. We used band 7 in detecting burnt area to minimize commission error. The following is the algorithm to detect deforestation caused burnt area.

\[
((B8(OI)-B12(OI))/(B8(OI)-B12(TI))-(B8(TI)-B12(TI))/(B8(TI)-B12(TI))) > 0.4 \text{ and } B7(TI)-B7(OI) < 1500 \tag{2}
\]

Where

- \(B7(OI)\) = Band 7 on original image
- \(B7(TI)\) = Band 7 on target image
- \(B8(OI)\) = Band 8 on original image
- \(B8(TI)\) = Band 8 on target image
- \(B12(OI)\) = Band 12 on original image
- \(B12(TI)\) = Band 12 on target image

Figure 10. Reflectance values of a pixel on forest to burnt area (dark brown).
Figure 11. Reflectance values of a pixel on forest to burnt area (light brown).

In detecting deforestation for Sentinel-2, we combine equations 1 and 2. First, we identify burnt area using the difference of the NBR on target image and original image, and the difference of band 7 on target image and original image. Second, we detect deforestation using the difference of band 4 on target image and reference image, the difference of band 11 on target image and reference image, and NDVI on original image. The result of first and second steps will be classified as deforestation. Otherwise, it will be identified as non-deforestation. The detail of these steps is described more detail in figure 12.

Figure 12. The flowchart of deforestation detection for Sentinel-2

3.2. Accuracy assessments
To assess the reliability of the MDD algorithm, we used visual and statistical assessments. From the figures of the MDD results, we evaluated them by using visual inspection. This assessment is general evaluation. Moreover, we used statistical assessment to inspect more detail the accuracies of the results.
In statistical assessment, we used confusion matrix [20] which can derive commission error [8] and omission error [21, 22]. This evaluation shows how much failure percentage of the MDD algorithm detects deforestation. To conduct the evaluation, a reference data which is the reference for assessment is needed. We generated the reference data by using manual digitation to provide the reference data to be more accurate.

We selected some samples from each environment with different land cover to evaluate the accuracy of cloud and cloud shadow masking. In fact, it was difficult to do interpretation for clouds and cloud shadows especially in the edge of cloud and cloud shadow. Therefore, we selected clouds and cloud shadows which have a distinct edge. The reference data for this assessment was generated by using manual digitation. We digitized the cloud and cloud shadow on the image samples manually.

4. Results and discussion

In this study, the MDD was used for detecting deforestation in some areas in Kalimantan Timur Province and Kepulauan Riau Province between 2018 and 2019 (see figure 2). The MDD was applied in some scenarios for Sentinel-2 in Kalimantan Timur Province. Deforestation occurred in this area from forest to other land covers. In visual assessment, we can see clearly in figure 13 that MDD algorithm can detect deforestation from forest to land clearing for plantation (yellow rectangle in figure 13(b)). However, the land clearing area is a bit difficult to detect as it has bright and dark objects, the MDD can detect it accurately.
Figure 13. The Sentinel-2 images in 2018 (left). The Sentinel-2 images in 2019 (middle). The results of MDD for Sentinel-2 images between 2018 and 2019 (right). Yellow, orange, blue, and light green rectangles indicate deforestation from forest to land clearing for plantation, forest to urban, forest to road, and forest to open land respectively.

The MDD can also detect deforestation from forest to urban. It can be seen in figure 13 shown by orange rectangles that the MDD can detect deforestation from forest to urban properly. It can detect deforestation from forest to road/small road accurately in figure 13 as well.
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Figure 14. Deforestation detection from forest to burnt area. (a) original image; (b) target image; (c) burnt area detection using dBNR; (d) burnt area detection using dBNR and band 7.

On the other hand, the dNBR was also applied in detecting deforestation from forest to burnt area in Kepulauan Riau Province between 2018 and 2019 (see figure 14). In this figure, we can see that if we use dNBR, the results of deforestation detection are accurate in burnt area, but the commission error is quite high because some area of dry river and cloud were identified as deforestation (see figure 14(c)). Therefore, we used band 7 in detecting burnt area to minimize commission error. After adding band 7 (see figure 14(d)), the dry river (see yellow circles) and cloud (see blue circle) are not detected as burnt area. In this scenario, the algorithm detected burnt area with dark brown and light brown colours. We can see that all burnt areas on the images were detected accurately after we combine dNBR and band 7.

Figure 15. (a) Target image; (b) Target image + reference data; and (c) MDD result + reference data.

In statistical assessment, confusion matrix (see Table 2) was applied to generate the errors and accuracies of the MDD results in identifying deforestation. Table 3 shows that commission error of deforestation detection is 0.63%. It is quite small and is occurred mostly in the area inside deforestation class. The algorithm detected forest as deforestation in the area. On the other hand, the omission error is 0.33%, and is smaller than commission error. It happened mostly while the MDD algorithm identify road (deforestation from forest to road) as non-deforestation, especially damaged roads. The pixels represent roads are similar to the vegetation/forest around these roads. As the errors are quite small, it makes both of the user’s accuracy and producer’s accuracy are quite high.
Table 2. Confusion matrix of the MDD results in detecting deforestation

| Classified Data | Reference Data | | |
|-----------------|----------------|---|---|
|                 | Deforestation  | Non-deforestation | |
| Deforestation   | 19954          | 126           | |
| Non deforestation| 67             | 30478         | |

Table 3. Errors and accuracies of the MDD results in detecting deforestation

|                      | Deforestation | Non-deforestation |
|----------------------|---------------|-------------------|
| Commission error     | 0.63%         | 0.22%             |
| Omission error       | 0.33%         | 0.42%             |
| User’s accuracy      | 99.37%        | 99.78%            |
| Producer’s accuracy  | 99.67%        | 99.58%            |

The advantage of the MDD is that this approach can minimize the effect of cloud and cloud shadow on the images. For instance, in figures 13 and 14, the cloud and cloud shadow on the original and target images did not interfere in detecting deforestation. Another advantage is that the MDD is automatic algorithm. Therefore, it can be used for a big dataset and can be used to support for forest monitoring in Indonesia which has very large of forest area.

5. Conclusion and future research

In this study, we proposed an approach for detecting deforestation. In band selection, we found that bands 4 and 11 of Sentinel-2, and combined them with NDVI, and dNBR to detect deforestation. As a result, the results of deforestation detection by using MDD have significantly high accuracies. Thus, this algorithm can be used to be an alternative method to detect deforestation for Sentinel-2 images. The advantage of the MDD algorithm is that it does not interfere cloud and cloud shadow in the original image. As it is an automatic algorithm, it can support in detecting deforestation for a big dataset. The MDD shows the ability in detecting deforestation in some scenarios in this study. However, there are still many kinds of forest in Indonesia or global area which did not discuss in this paper. Therefore, in the future research, we would like to test the proposed method for many kinds of forest in entire Indonesia or global area.

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