Assessment of cloud-free normalized difference vegetation index data for land monitoring in Indonesia

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ABSTRACT

Continuous land monitoring in Indonesia using optical remote sensing satellites is difficult due to frequent clouds. Therefore, we studied the feasibility of monthly land monitoring during the second half of 2019, using moderate resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI) data from Terra and Aqua satellites. We divide the Indonesian area into seven regions (Sumatra, Java, Kalimantan, Sulawesi, Nusa Tenggara, Maluku, and Papua) and examine NDVI data for each of the regions. We also calculated the cloud occurrence percentage every hour using Himawari-8 data to compare cloud conditions at different acquisition times. This research shows that Terra satellite provides more cloud-free pixels than Aqua while combining data from both significantly increase the cloud-free NDVI pixels. Monthly monitoring is feasible in most regions because the cloudy areas are less than 10%. However, in Sumatra, the cloudy area was more than 10% in October 2019. We need to include further data processing to improve the feasibility of continuous monitoring in Sumatra. This research concludes that monthly monitoring is still feasible in Indonesia, although some data require further processing. The use of additional data from other satellites in the monitoring can be an option for further research.

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1. INTRODUCTION

Land monitoring is important in supporting decision-making on land management [1]. The application may include monitoring in agriculture [2]–[4], forestry [5], [6], urban areas [7], [8], disaster susceptibility and hazards [9], [10]. In addition to monitoring the inner mainland, observation of the coastline and its change is also important to monitor the impacts of disturbances in coastal areas [11], [12].

In Indonesia, monitoring land area is challenging. The large area of Indonesia makes the use of low-spatial-resolution remote sensing satellites important [13]. Although the satellites are able to capture a large area, the characteristics of Indonesia as a tropical region make the occurrence of clouds frequent, especially around equatorial regions [14]. The clouds block solar radiation, and the optical sensors on satellites cannot capture images of ground objects. It makes monitoring more difficult in Indonesia. The utilization of images from optical sensors is more popular than the use of radar data because the interpretation of the data from optical sensors is easier. The advantage of using radar is that the electromagnetic waves in the radar system can pass through the clouds. Unfortunately, there are limitations on the process of intuitive interpretation of the radar data [15]. Since there is no exact guidance to use optical remote sensing data in terms of the cloud problem, we try to do an assessment on how continuous land monitoring can be performed in Indonesia using optical remote sensing satellites.

The vegetation index information derived from optical satellite images can be used as a parameter in land monitoring. The familiar one is the normalized difference vegetation index (NDVI) [16]–[18]. A high NDVI value indicates high vegetation density, while a low value indicates low vegetation density and might be in the form of barren land or a wet area. The vegetation index naturally represents the health of vegetation over an area; moreover, this parameter can also be used to represent the land cover type [19], [20]. One of the sources for acquiring NDVI data is the constellation of Terra and Aqua satellites. The satellites were launched for environmental monitoring with global coverage and brought the moderate resolution imaging spectroradiometer (MODIS) payload onboard [21]. The satellites acquire 36 spectral bands from the sensor, and algorithms to estimate the value of bio-geo-physical parameters from the data have been well developed [22]–[24]. The two satellites cross the equator at different local times. Both satellites have a short repetition time period to provide an image of the whole world in one or two days. Therefore, in this research, we observed the availability of cloud-free NDVI data derived from the Terra and Aqua satellite data.

Previous research has observed cloud-free pixels from another low-spatial-resolution satellite (Himawari-8) over Java, then calculated aggregates and performed spatial interpolation to available pixels. The research focuses on dynamic variables [25] instead of slower change parameters like NDVI. While Himawari-8 has advantages in temporal resolution, the study on NDVI data derived from Himawari-8 continues. That's why we do not use Himawari NDVI in this research. Other research observed 8-day composite MODIS data over a global area, which shows that Indonesia has a low percentage of clear view during the agricultural growing season [26]. Gastellu-Etchegorry (1988) observed Landsat and SPOT data to estimate the probability of acquiring images with specific cloud cover [27]. The research did not provide the probability of having a cloud-free image with full spatial coverage of Indonesia. As a novelty in this research, assessments were made with monthly data for various regions of Indonesia. Low-spatial-resolution satellite images are used to provide spatial data with larger coverage and shorter repetition times. Monthly periods of continuous monitoring will be examined instead of 8-day periods. A longer period may provide more cloud-free data and increase the feasibility of continuous land monitoring in Indonesia. This study will suggest whether MODIS data are suitable for monthly monitoring in different regions of Indonesia. This study will also explain the effects of satellite constellations at different acquisition times. The probability of cloud occurrence per hour was calculated and used in the analysis to compare each satellite in the constellation. Advice for how to perform the monthly monitoring will be carried out considering the result of the assessment.

2. METHOD

This research's study area includes the whole of Indonesia, with an observation period in the second semester of 2019. The period is selected to circumscribe the research on a time span without strong influence from El Nino and La Nina. The second semester was selected because the peak rainfall time in various regions appeared during that time [28]. We divide the area into seven regions, including the small islands around each of them. The regions are Sumatra, Java, Kalimantan, Sulawesi, Nusa Tenggara, Maluku, and Papua shown in Figure 1.

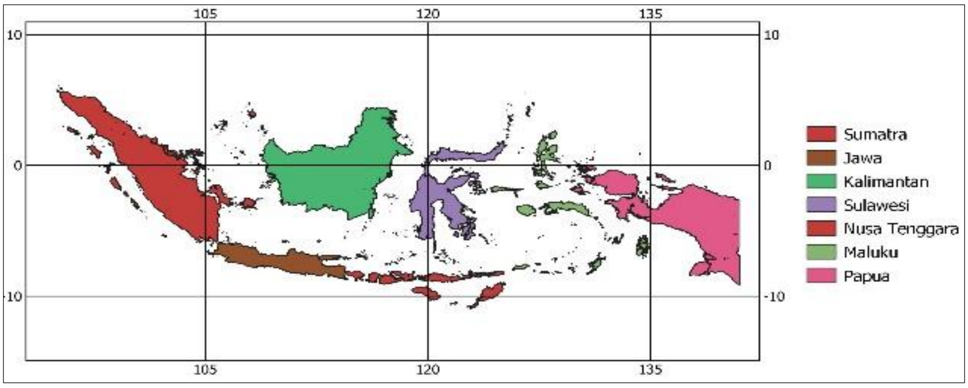


Figure 1. Seven regions of the study area

NDVI data was acquired from the MODIS sensor between July and December 2019 from the Terra and Aqua satellites. Terra crosses the equator at 10.30 a.m. local time, while Aqua does so at 1.30 p.m. Those equatorial crossing times are generally applied in many remote sensing satellites [29]. At those times, the sun's radiation is not at its peak. Therefore, the sensors on the satellite are suitable to capture interpretable images [30]. The NDVI data for this study was downloaded from Google Earth Engine (GEE) and consists of monthly NDVI data from Terra (MYD13A3 collection) and Aqua (MOD13A3 collection). Although MODIS data was acquired at 250 m, 500 m, and 1 km spatial resolution, NDVI was calculated at 1 km spatial resolution. NDVI is calculated using reflectance values in the red band and Near Infrared (NIR) band [31]. The data also include QA with a 4-bit flag, where QA values of one in the 3rd and 4th bits represent cloudy pixels. This research also uses Himawari-8 High-resolution Cloud Analysis Information (HCAI) data, which contains cloud-type information provided by JAXA via the Indonesian Meteorology, Climatology, and Geophysical Agency (BMKG). Cloud-type information is represented by a numerical value. A zero value means a cloud-free pixel, while other values indicate different types of clouds. HCAI data is derived from Himawari-8 level-1 data [32] and calculated hourly. HCAI data has a spatial resolution of 2 km, lower than MODIS NDVI data. The difference in spatial resolution between HCAI and MODIS NDVI data is assumed to be acceptable because each region in the study area has a large coverage area.

Evaluation is performed in two parts. First, the cloud percentage is calculated monthly using HCAI data over the seven regions. The result will give insight into the probability of having a cloud-free image between each region at different months and different acquisition times. Second, monthly NDVI data per month per region will be examined and compared based on the operational satellites (Terra only, Aqua only, and both). When a combination of both satellites is used, mosaicking of NDVI data is performed per pixel. Masking is carried out using the cloud information provided in each of the NDVI data from the two satellites. An evaluation is then carried out to determine which NDVI data can be used to monitor each region in Indonesia. The flowchart for this research is shown in Figure 2.

Assessment is performed in two parts (Figure 2). First, monthly NDVI data will be examined based on the operational satellites (Terra only, Aqua only, and both). Masking is carried out using the cloud information provided in each of the NDVI data from the two satellites. When a combination of both satellites is used, mosaicking of NDVI data is performed pixel by pixel. The percentage of cloudy area is then calculated for each region using NDVI data from Terra only, Aqua only, and both satellites.

Second, the percentage of the cloudy pixels per hour is calculated monthly using HCAI data over the seven regions. The number of cloudy pixels is divided by the total number of pixels over the region in one month with the same observation time. The result will give insight into the probability of having a cloud-free image between each region at different months and different acquisition times. To observe data from the Terra and Aqua satellites, it is assumed that the satellites are crossing the equator at the same longitude coordinate of the centroid in each region. Knowing the centroid coordinates of every region, we can calculate the time difference between the centroid and Greenwich meridian. A distance of 15 degrees of longitude is equal to a difference of one hour. A time difference at a distance of less than 15 degrees is calculated proportionally. Using information of the time difference and local equatorial crossing times, the equatorial crossing times in coordinated universal time (UTC) can be calculated for the Terra and Aqua satellites.

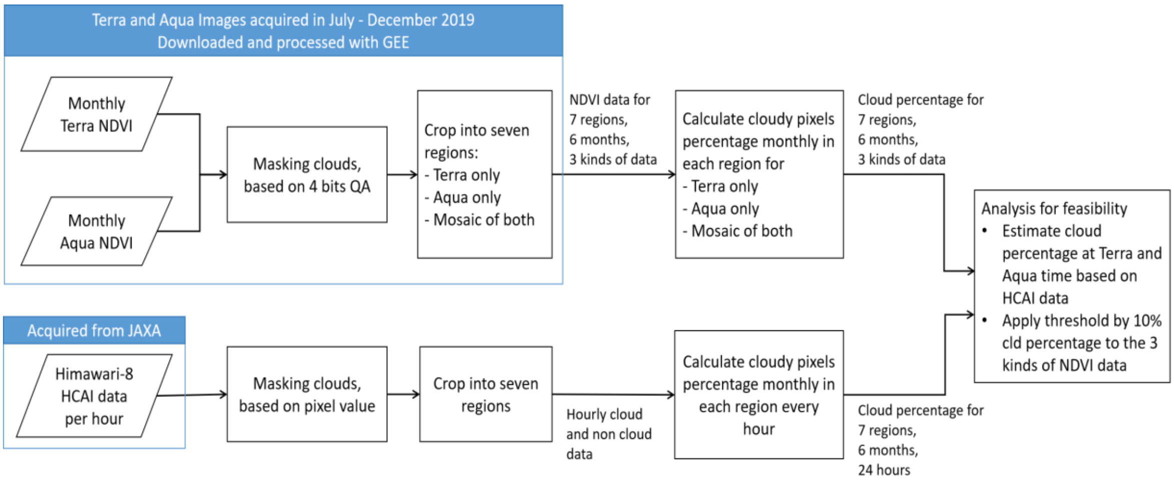


Figure 2. Flowchart of the assessment

Based on the assessments, analysis is performed to indicate which satellite can provide appropriate data for monthly land monitoring in various regions. A 10% threshold to cloudy area percentage is used to decide whether monthly land monitoring is feasible. When the cloudy area percentage in a region is less than or equal to 10%, interpretation can probably be well performed [33].

3. RESULTS AND DISCUSSION

Cloud-free data availability is examined by calculating the percentage of cloudy areas. The percentage of cloudy areas over the seven regions is calculated using monthly NDVI data from Terra only, Aqua only, and the mosaic of both satellite data, shown in Table 1.

Table 1. Cloudy area percentage in the seven regions based on MODIS NDVI July–Des 2019

Region and satellite	Cloudy area percentage					
	July	August	Sept	Oct	Nop	Des
Sumatra						
Terra	1.84	2.44	10.91	35.35	14.04	21.85
Aqua	3.16	4.87	14.25	24.62	17.91	22.21
Terra - Aqua	0.48	0.69	3.47	13.31	4.79	7.99
Jawa						
Terra	0.23	0.35	0.65	1.02	1.08	7.82
Aqua	0.77	0.86	0.98	0.98	2.20	34.67
Terra - Aqua	0.18	0.17	0.19	0.25	0.41	3.72
Kalimantan						
Terra	4.43	5.84	7.43	24.75	18.33	20.53
Aqua	1.72	4.00	7.35	7.70	6.36	16.45
Terra - Aqua	0.50	0.88	1.64	3.36	2.18	4.98
Nusa Tenggara						
Terra	1.06	0.92	0.95	1.19	1.35	1.73
Aqua	1.11	0.90	0.95	1.00	1.22	9.85
Terra - Aqua	0.27	0.22	0.23	0.29	0.34	0.58
Sulawesi						
Terra	4.47	1.81	1.58	3.43	3.17	7.66
Aqua	9.31	5.91	1.94	4.62	6.28	23.29
Terra - Aqua	1.82	0.63	0.37	0.89	1.05	3.60
Maluku						
Terra	14.66	9.14	8.55	12.10	4.39	3.67
Aqua	14.60	15.72	7.23	9.80	4.37	8.46
Terra - Aqua	6.93	4.92	2.71	3.55	0.97	1.26
Papua						
Terra	19.21	12.85	12.35	16.31	9.81	2.21
Aqua	21.04	16.49	11.32	12.88	9.55	8.32
Terra - Aqua	7.89	4.08	3.25	3.82	2.45	0.74

From Table 1, it is shown for each region as follows:

- In Sumatra, the percentage of cloudy areas is generally higher than in other regions, especially from October up to December. Combining data from the two satellites increases cloud-free data availability, but the percentage of cloudy areas is still high in October, reaching around 13%.
- The percentage of cloudy areas in Java is relatively small using data from any of the satellites, except in December when using data from Aqua. Combining data from the two satellites increases cloud-free data availability, with the highest percentage of cloudy areas being lower than 4% in December.
- In Kalimantan, the percentage of cloudy areas is a bit higher when using data from Terra rather than Aqua. Combining data from the two satellites increases cloud-free data availability, with the highest percentage of cloudy areas being lower than 5% in December.
- In Nusa Tenggara, the percentage of cloudy areas is relatively small, just like in Java. The percentage was also higher in December, according to data from Aqua. Overall, the percentage of cloudy areas in Nusa Tenggara is the smallest among the seven regions. This result is in line with research by Hidayat *et al.* [34]. Combining data from the two satellites increases cloud-free data availability, with the highest percentage of cloudy areas being lower than 1% in December.
- In Sulawesi, the percentage of cloudy areas using data from Terra is smaller than using data from Aqua, especially in December. It is similar to conditions in Java and Nusa Tenggara. Combining data from the two satellites increases cloud-free data availability, with the highest percentage of cloudy areas being lower than 4% in December.

- In Maluku, the percentage of cloudy areas is a bit high even when using data from any of the satellites and overall, using data from Terra results in a smaller percentage of cloudy areas, with a generally decreasing value from July to December. Combining data from both satellites increases cloud-free data availability, with the highest percentage of cloudy areas being lower than 7% in July.
- In Papua, the percentage of cloudy areas is a bit high, similar to Maluku, and generally decreases from July to December using data from any of the satellites. Combining data from both satellites increases cloud-free data availability, with the highest percentage of cloudy areas being lower than 8% in July.

Information about the percentage of cloudy pixels during the diurnal cycle is crucial to compare the impact of using data from Terra or Aqua. The calculation of cloudy pixels percentage per hour based on HCAI data is presented in Figure 3 (see in appendix). We also mark the time on the graph in Figure 3 when Terra and Aqua satellites crossed the equator (indicated by T for Terra and A for Aqua). It assumes that the longitude coordinate when satellites cross the equator is the same as the centroid's longitude for each region. Figures 3(a), 3(c), and 3(g) also shows that the cloudy pixels percentage is closely similar at Terra's crossing time and Aqua's crossing time over three regions (Sumatera, Kalimantan, and Papua). In the other four regions (Java, Nusa Tenggara, Sulawesi, and Maluku), the cloudy pixels percentage is lower at Terra's crossing time (Figures 3(b), 3(d), 3(e), and 3(f)). The conclusion might be slightly inaccurate since MODIS data has a large swath width. It means that satellite trajectories might be a bit far from the centroid longitude of each region. In Kalimantan (Figure 3(c)), the graph shows that the percentage of cloudy pixels decreased after the Aqua crossing. As a result, the percentage of cloudy pixels will probably become lower if data from Aqua is used.

Both results from Himawari HCAI and monthly MODIS NDVI show conformity. Terra satellite crossing the equator in the morning provides more cloud-free pixels than Aqua, as shown in both assessments. Combining data from Terra and Aqua significantly decreases the cloudy area. By simulating a threshold of 10% as the maximum cloudy area percentage [33], it is shown that only Sumatera has a cloudy area percentage outside the criteria. Monitoring land on Nusa Tenggara may use data from any of the satellites. Monitoring on Java and Sulawesi may use data from Terra or both. It is suggested that data from both satellites be used to monitor land on Kalimantan, Maluku, and Papua. Monthly monitoring in Sumatra will most likely be difficult, even if using NDVI data from both satellites. Combining NDVI data from Terra and Aqua did not produce sufficient data for monitoring Sumatra in October. As an alternative to utilizing October data from Sumatera, several reconstruction techniques have been observed. Vybornova (2018) shows that reconstruction can be applied with good accuracy when the cloudy area percentage does not exceed 30% [35]. Criminisi *et al.* [36] use the exemplar-based impainting method to restore images with missing areas of around 20%. The distribution of clouds in the Sumatra region in October 2019, which has the largest cloudy area using data from both satellites (13.31%), is shown in Figure 4. The cloudy area is located on the northern island, whereas Lampung, which is in the south, close to Java, is mostly cloud-free. The frequent cloud occurrence on the north of Sumatra in October might be affected by the Asian monsoon, which is starting to bring humid air from the ocean. The south of Sumatra is still affected by the Australian monsoon, which brings dry air from the Australian continent.

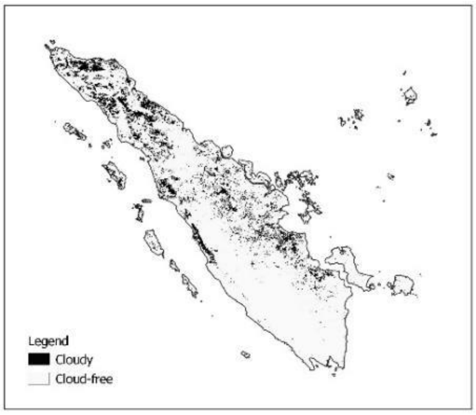


Figure 4. Cloud coverage over Sumatra in October 2019 based on MODIS NDVI data

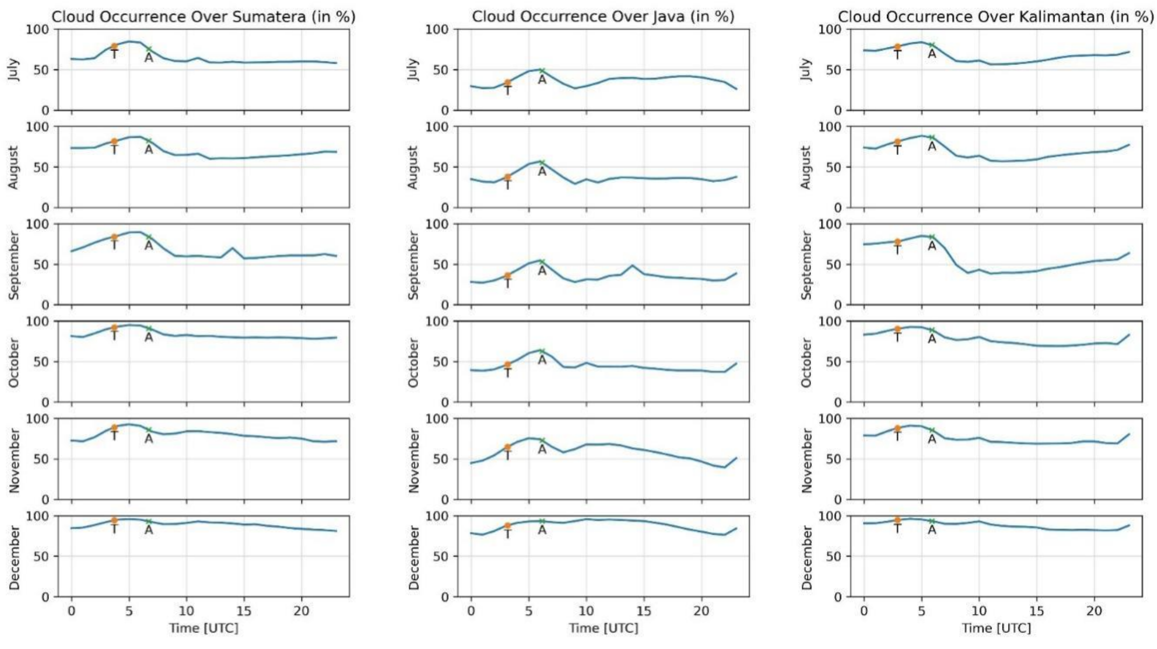
Examining the cloudy pixels percentage month-by-month from July to December (Figure 3) shows that this research conforms to the climatic characteristics in Indonesia. In Sumatra, the percentage of cloudy pixels is generally high, especially in October. In Java, Kalimantan, and Nusa Tenggara, the percentage of cloudy pixels is generally increasing and will reach its highest in December. The cloudy pixels percentage is decreasing in Sulawesi until September, then increasing and reaching the highest in December. In Maluku, the percentage of cloudy pixels decreases until November and then increases a little bit in December. In Papua, the percentage of the cloudy pixels keeps decreasing until December. This result is in line with the climatic region in Indonesia [28], which divides Indonesia into three regions with different peak rainfall amounts. Among the regions, the cloudy pixel percentage is relatively lower in Java and Nusa Tenggara and higher in Sumatra, Kalimantan, and Papua.

While other research mostly focuses on observation in Java or specific areas using MODIS, this research provides comprehensive research for the whole of Indonesia. The result of this research shows that monthly observations over Indonesian land might be performed with direct interpretation in most regions, while in some places, like northern Sumatra in October, it may probably need further processing.

4. CONCLUSION

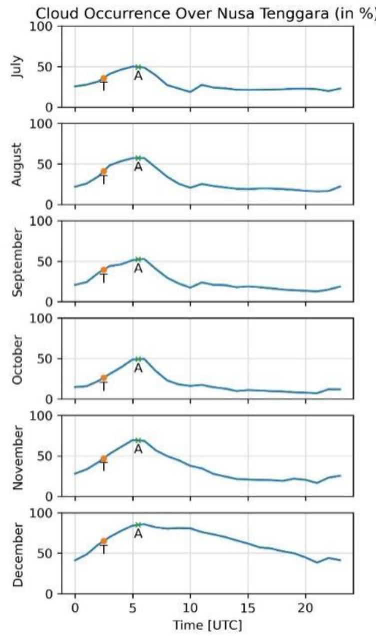
The assessment was made of all regions in Indonesia using monthly MODIS NDVI data for land monitoring. It has been shown that continuous monitoring might be performed in all regions of Indonesia. Data in most regions can be used for direct interpretation, while other areas may need further data processing, i.e., image reconstruction, due to the high percentage of cloudy areas. This research also shows that the satellite constellation, which acquires images on the same day at different times, may increase cloud-free data availability. Meanwhile, Terra, which captures images in the morning, provides more cloud-free pixels than Aqua. This study may help decision-makers manage land observation strategies in Indonesia using optical remote sensing satellites. The use of additional data from other satellites can be an alternative to increasing data availability. A longer period of data observation should also be considered in further research to increase the reliability of this study.

APPENDIX

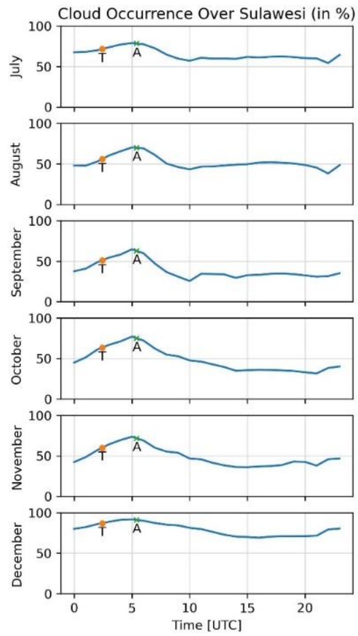


(a) (b) (c)

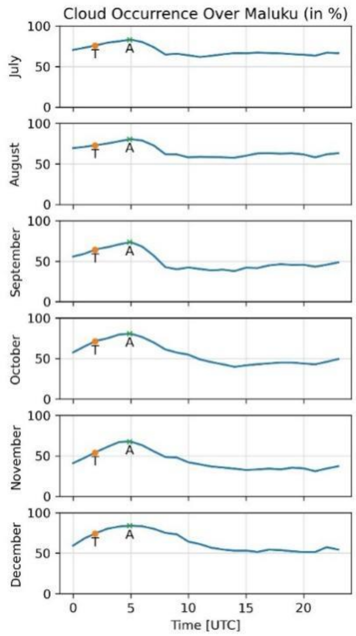
Figure 3. Monthly cloudy pixels percentage from HCAI data and position of Terra (T) Aqua (A) equatorial crossing time over (a) Sumatera, (b) Jawa, (c) Kalimantan



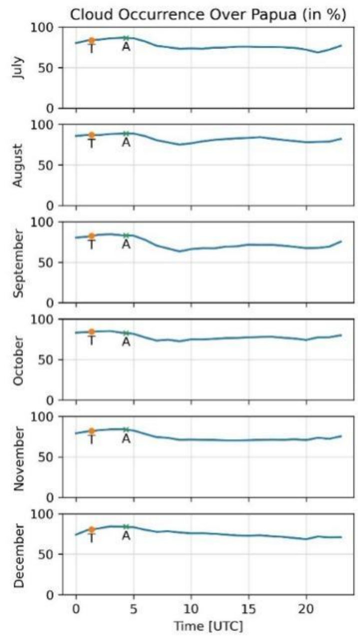
(d)



(e)



(f)



(g)

Figure 3. Monthly cloudy pixels percentage from HCAI data and position of Terra (T) Aqua (A) equatorial crossing time over (d) Nusa Tenggara, (e) Sulawesi, (f) Maluku, and (g) Papua (*Continue*)

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