Land clearing area prioritization using GLAD alert data to prevent peat fires in South Sumatera, Indonesia

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Abstract. Peatland clearing and draining are associated with many peat fires in South Sumatera. In 2020 we developed prioritization of peatland clearing areas using GLAD alert data to prevent catastrophic peat fires. GLAD alert data is near real-time alerting system that detects loss of trees, produced by University of Maryland and Global Forest Watch. This research aims to get prioritized area indicating land clearing and to test its reliability to prevent peat fires in South Sumatra. A total of 634 cluster areas indicating peatland clearing were found in between July and September 2020, which 20 of those cluster areas are selected for validation (ground truth). Validation was conducted by field survey and flying Unmanned Aerial Vehicle (UAV) in 3 districts, namely Musi Rawas Utara, Banyuasin, and Ogan Komering Ilir. The survey confirmed that 19 clusters experienced forest fires, land clearing, and rejuvenation of plantation. Meanwhile, the others became savanna from previous forest fires and former land clearing by burning. Prioritization areas using GLAD alert data was capable to detect land clearing, but further study is needed to predict peat fires due to peatland clearing.

1. Introduction

Tropical peatland is a major carbon-rich ecosystem that stores almost 20 percent of global carbon stocks (around 81.5-91.8 GtC) despite covering only 11 percent of global peatland area [1,2]. In Indonesia, this ecosystem is distributed in Sumatera, Kalimantan, and Papua, covering approximately 15 percent of total land area [3]. As one of the major carbon sinks, peatland ecosystem plays an important role in climate change, provides ecological services and valuable socio-economic benefits from local to global scale. However, over a few decades tropical peatland in Southeast Asia have undergone rapid transformation due to anthropogenic pressure, such as logging, peatland conversion to large-scale agriculture and industrial plantation, and construction of artificial drainage canals [4–6]. Consequently, this vulnerable ecosystem is massively degraded and susceptible to fires which accelerates the release of greenhouse gas emissions to the atmosphere.

In Indonesia, peatland degradation caused by land clearing and excessive draining is often associated with recurrent peat fires. According to Page et al. [7] peatland conversion to plantation has been shown to go hand-in-hand with the increase of fire occurrences and the decrease of fire resilience. Fire is often
used for land clearing by both industrial and smallholder farmers [8,9]. This slash-and-burn method is relatively safe when peatland is still in wet condition and is done only on top layer of the peatland [10]. But when it is done in the already dried peatland, such agricultural practice can cause large peatland fires, especially in the dry season. Several studies stated that massive land conversion to plantation, shifting cultivation and permanent agricultural activities are the main causes of 1997/1998 fires, which resulted in the released of 0.81 to 2.57 GtC greenhouse gas emissions into the atmosphere [11–13].

Monitoring is an important step to obtain information on the peatland condition and to identify the risk of peatland degradation [14]. For this purpose, remote sensing and GIS has contributed to monitor large-scale areas and utilized to support forest and fire monitoring [15]. GLAD alert data, developed by University of Maryland from Landsat 7 ETM+ and Landsat 8 OLI/TIRS, have been used to monitor forest. The data can support monitoring forest disturbances by detecting removal of tree cover in near real-time [16]. In this study we proposed an approach to prioritize land clearing areas in peatland in South Sumatera using GLAD alert data and GIS to prevent catastrophic peat fires.

2. Data and methods

2.1. Study sites
The study site is situated in 1.23 Mha of peatland areas, covering 7 districts of South Sumatera province. This peatland is divided into 2 classes, approximately 0.97 Mha protected peatland area and 0.26 Mha cultivated peatland area, and it lies across protected forest, production forest, and non-forest areas (APL).

![Figure 1. Study location situated in protected and cultivated peatlands of South Sumatera province.](image)

2.2. Data and sources
This study employed GLAD alert data, a near real-time Landsat-based tropical forest disturbance alert with spatial resolution of 30 meters. GLAD alert data is produced by University of Maryland that can be accessed through Global Forest Watch platform (globalforestwatch.org). The data are available for all parts of Indonesia.

GLAD alert data are developed from Landsat 7 ETM+ and Landsat 8 OLI using a theme-based alerting system. Both Landsat 7 ETM+ and Landsat 8 OLI have temporal resolution of 16 days and pair application of them enables updated the data every 8 days while maintaining its medium spatial resolution (30 meters). This alert system defines forest cover as 5-meters vegetation with more than 60
3 percent of canopy closure. An alert is defined as any Landsat pixel that undergone vegetation canopy loss for more than 50 percent [16]. However, this data also comes with limitation. As any alert system based on optical satellite imagery, GLAD alert data may be delayed due to persistent cloud cover. Furthermore, this alert data cannot differentiate between human-induced forest disturbances and natural disturbances (such as landslides or flood), as well as unable to specifically determine the cause of such disturbances, either land clearing or seasonal harvesting.

GLAD alert data consists of 2 (two) type of alerts, namely ‘possible’ and ‘confirmed’. If the system identifies pixels experiencing forest loss without antecedent alert, then the alerts are labelled as ‘possible’. Alerts are labelled as ‘confirmed’ if pixels experience forest loss in two or more observations. In this study, we used both ‘possible’ and ‘confirmed’ alerts to maximize their use in detecting land clearing. GLAD alert data were then filtered within period of 1 July 2020 to 8 September 2020.

As for pre-validation process, we used publicly available high-resolution optical satellite imageries, such as Sentinel-2 (10-meter spatial resolution) and Planet monthly mosaic (3-to-5-meter spatial resolution). To support the analysis, we used several additional maps that can be seen in Table 1.

### Table 1. Additional maps used in land clearing prioritization analysis.

| Data                        | Source                                                                 | Year | Description                                                                                                                                 |
|-----------------------------|-------------------------------------------------------------------------|------|------------------------------------------------------------------------------------------------------------------------------------------|
| Indonesia Peatland Map      | Indonesian Center for Agricultural Land Resources Research and Development (ICALRRD) | 2011 | Map of Indonesia peat extent and depth in 1:250.000                                                                                  |
| Peat Ecosystem Function Map | Ministry of Environment and Forestry, accessed through geoportal.menhk.go.id in September 2020 | 2017 | Map of indicative peatland ecosystem function in 1:250.000, dividing peatland ecosystem into 2 (two) classes based on its ecological function, i.e. protection and cultivation areas |
| Peat Hydrological Unit Map  | Ministry of Environment and Forestry, accessed through geoportal.menhk.go.id in September 2020 | 2017 | Map of peat hydrological unit in 1:250.000                                                                                                  |
| Forest Area Map             | Ministry of Environment and Forestry, accessed through geoportal.menhk.go.id in September 2020 | 2019 | Map of forest area, consists of 7 (seven) classes, i.e. converted production forest, limited production forest, production forest, national park, protected forest, wildlife reserve, and other utilization area (APL) |
| Indonesia Administrative Map| Geospatial Information Agency, accessed through portal.ina-sdi.or.id in April 2021 | 2020 | Village levels administrative map in 1:10.000                                                                                              |

#### 2.3. Prioritization analysis

In this study, GIS analysis was used to identify any indication of land clearing and to prioritize the areas to be validated. The analysis was carried out in 2 (two) main steps, namely clustering and filtering analysis. We used density-based spatial clustering of applications with noise or DBSCAN for clustering. This clustering algorithm is widely used in many spatial analyses to group geospatial phenomenon. DBSCAN is useful to detect outliers of a dataset. Moreover, we overlaid the point clusters with additional maps to extract more information and to filter the point clusters based on necessity. In
principal this filtering approach is similar to Places to Watch workflow proposed by Weisse et al. [17], but we only used number of points within clusters as a basis to prioritize the most concerning areas.

DBSCAN is a hierarchical clustering algorithm based on density points. We basically partitioned set of data points into dense regions and not-so-dense regions. This algorithm works based on 2 (two) concepts of directly density-reachability and density-connectivity [18]. Therefore, DBSCAN algorithm relies on 2 (two) predetermined parameters; the maximum Euclidian distance of neighborhood points (Eps or Epsilon) and the minimum number of points in an Eps-neighborhood (minPts). These parameters will then be used to determine the shape and size of clusters of points.

In this study, pixel-based GLAD alert data were converted into a set of vector point data. Based on our best practices, we set the number of Eps and minPts with 0.001 degree (or 4 times the size of GLAD alert pixel) and 9, respectively. Such vector point data were then analyzed by using DBSCAN in an open-source Quantum GIS software. The result of clustering was several sets of point clusters and outliers separated in different classes. We then ranked the cluster classes based on the highest number of alert points within each class to get the prioritized areas.

2.4. Field validation
Ground-based measurement is essential to avoid false-positive alerts. In this study, such ground-based measurement included field observation to validate and to gather several information, such as actual land condition, land status, drivers of land clearing, time and subject of land clearing, and existence of drainage canals. Aerial drone mapping, peat soil sampling, and short interview to local authorities were conducted for validation.

The validation was carried out in 3 regencies of South Sumatera, namely Musi Rawas Utara, Banyuasin, and Ogan Komering Ilir (OKI). Aerial drone mapping was performed once in centroid area of 800 m x 800 m. We managed to flight above center of clustering area as much as possible. When we were unable to access to center of area, we flew drone in the edge of cluster area or as near as possible to the clustering area to get side view image. Moreover, we drilled the land surface to observe the depth of peat and for peat soil sampling. At the same location with the drone map area, we drilled 5 (five) points at the center, north part, south part, west part, and east part. The horizontal distance to the center points was at least 30 m.

3. Results and discussion

3.1. Indicative land clearing areas from GIS analysis
From DBSCAN clustering analysis, we detected 4,282 clusters of GLAD alerts across South Sumatera province within period 1 July 2020 and 8 September 2020. This clustering process also detected 77,810 GLAD alerts that have been classified as outliers by DBSCAN clustering algorithm. We then filtered those GLAD alert clusters only within peatland areas. The result was 634 clusters of alerts, which classified as indicative land clearing areas in South Sumatera peatland area.

From these 634 alerts, we ranked the top 20 clusters based on the highest number of alerts within each cluster. These top 20 clusters were grouped into 5 different locations to simplify field validation that can be seen in Table 2. The distribution of all clusters is provided in Figure 2.
Table 2. Five locations of field validation and their area estimation.

| Location | Administrative locations | Peat Hydrological Unit (PHU) | Land clearing areas estimation (in hectares) |
|----------|--------------------------|-----------------------------|---------------------------------------------|
| 1        | Karangdapo village, Musi Rawas Utara regency | Sungai Rumpit – Sungai Rawas PHU | 303.92                                      |
| 2        | Cengal village, Ogan Komering Ilir regency | Sungai Sibumbung – Sungai Talangrimba PHU | 43.29                                      |
| 3        | Across 2 villages (Air Solok Batu and Juru Taro village), Banyuasin regency | Sungai Musi – Sungai Saleh PHU | 88.61                                      |
| 4        | Across 2 villages (Ulak Kedondong and Cengal village), Ogan Komering Ilir regency | Sungai Sibumbung – Sungai Talangrimba PHU | 31.76                                      |
| 5        | Perigi village, Ogan Komering Ilir regency | Sungai Saleh – Sungai Sugihan PHU | 10.5                                       |

Figure 2. The distribution of 634 clusters of alerts (black dot) that were classified as indicative land clearing and 20 clusters of alerts (red dot) that were grouped into 5 locations to be validated. All these alerts were situated in peatland area of South Sumatera occurring within period of 1 July 2020 and 8 September 2020.

We then analyzed the 634 alerts by overlaying their locations and forest area map. Around 73 percent of these clusters were located at production forest area, 23 percent in other utilization area (APL) or non-forest area, and the remains were in protected forest, national park, and wildlife reserve area. The high number of alerts in production forest and non-forest area indicate forest utilization activities, such as seasonal harvesting, rejuvenation, or new land clearing for agriculture and plantation, in both large-scaled industry and locally managed plantation. Meanwhile, relatively small number of alerts in protection forest area can be flagged as ‘alert’ due to its forest status which is needed a closer look.
Figure 3. The distribution of 634 GLAD alerts based on forest area, with the number of alerts and their clusters were in production forest (73%), other utilization area (43%), and protected forest (4%).

3.2. Aerial drone mapping and soil sampling

Aerial drone mapping and soil sampling provided actual land condition to complement extracted information from remote sensing imageries. Based on ground-based validation in 5 locations, we found that 4 (four) locations that were indicated to be land cleared were valid while 1 (one) location in Perigi village was invalid (or false-positive alerts). Drone orthophotos and photos in the five locations can be seen in Figure 4.

Figure 4. Aerial orthophoto and photos of the 5 locations in (1) Karangdapo village, (2) Cengal village, (3) Air Solok Batu and Juru Taro village, (4) Ulak Kedondong and Cengal village, and (5) Perigi village in South Sumatera.
Peat soil sampling taken from peat soil drilling showed that 3 (three) of the sites were peatland, 1 (one) of them was mineral soil, and 1 (one) other cannot be classified due to limited accessibility (namely, location 4). The peat depths and peat soil maturities are presented in Table 3.

Table 3. Peat soil sampling in 5 locations.

| Location | Estimate range of peat depth (cm) | Peat maturity       |
|----------|----------------------------------|---------------------|
| 1        | 17 – 181 cm                      | Fibric – Sapric     |
| 2        | 176 – 200 cm                     | Fibric – Hemic      |
| 3        | 0 – 25 cm                        | Mineral soil        |
| 4        | No data                          | No data             |
| 5        | 50 – 180 cm                      | Fibric – Sapric     |

3.3. Main causes of the indicative land clearing
The alerts at Karangdapo village seem to relate with seasonal harvesting, followed by replanting in an oil palm plantation. According to local authorities, replanting was started in July 2020. This information was confirmed by our pre-validation using high resolution satellite imagery (Sentinel-2 and Planets) that indicated harvesting and replanting was started between June 2020 and September 2020. During field survey, this area had been planted with oil palm sapling, aged around 2 months old. In this area we also found drainage canals but none of vegetation litters were found.

At the second location in Cengal village, land clearing was the main trigger of the alerts. The activity was followed by digging new artificial canals for oil palm plantation. Prior to this newly oil palm plantation, this peatland area was covered by native swamp plants, such as gelam (*Melaleuca cajuputi*) and prepat (*Combretocarpus rotundatus*). During our field survey, vegetation litters could be found, and no indicative fire use in this area.

At the third location in Air Solok Batu village and Juru Taro village, the GLAD alerts seem to relate with land clearing. This land cleared area was situated in a protected forest of wetland ecosystem, dominated by nipah plants (*Nypa fruticans*). At the time of visits, the area was under fires, making the difficulties to take soil sample and drone photos. We found the use of heavy machine and canal drainage in the field. However, the drivers of fires remained unknown.

In the fourth location in Ulak Kedondong village and Cengal village, based on drone view, the GLAD alerts were caused by land clearing for oil palm plantation. However, we could not obtain the depth of peat because of the prohibition to enter the area at the time.

In the fifth location in Perigi village, we could not find any new land clearing or seasonal harvesting activities near the indicated location of GLAD alerts. Therefore, we classified this cluster as false-positive alert. One cluster area was in savanna field and the others were unproductive rice field being covered by shrubs.

4. Conclusion
In this study, we found 634 clusters of GLAD alerts in peatland in South Sumatera within the period of 1 July 2020 to 8 September 2020. These clusters were filtered into 20 clusters and grouped into 5 (five) locations. We found that 4 (four) locations of indicative land clearing were classified as valid while 1 (one) location in Perigi village was invalid (false-positive alerts). Such alerts related to seasonal harvesting followed by replanting, and new land clearing for oil palm plantation. By using GIS prioritization analysis, GLAD alert was capable to detect land clearing. Field validation was essential to
validate the cause of the alerts while gathering data from the ground. However, further study is needed to calculate the risk of peat fires induced by peatland clearing.

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