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Evaluating Visible–Infrared Imaging Radiometer Suite Imagery for Developing Near-Real-Time Nationwide Vegetation Cover Monitoring in Indonesia

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Abstract: The necessity for precise and current data concerning the dynamics of land cover change in Indonesia is crucial for efforts to reduce natural vegetation cover due to agricultural expansion. The functionality of monitoring systems that incorporate Terra-MODIS is currently compromised by the limited availability of data for the immediate future. This study seeks to assess the potential of VIIRS satellite imagery in developing an early warning system for monitoring vegetation cover change in Indonesia. The normalized differential open-area index (NDOAI) computed from 8-day VIIRS data was employed to detect changes in vegetation cover based on pixel-by-pixel subtraction in the NDOAI data time series. Evaluating the pixel-level accuracy of change detection is complicated due to the fact that we evaluate a change map at a coarser resolution than the Landsat-based reference map. The results revealed that increasing the threshold percentage is associated with improved accuracy. In change detection, there is often a trade-off between accuracy and sensitivity. A threshold that is too low may result in false positives, while a threshold that is too high may lead to missed changes. This study demonstrates that when a threshold value of less than 20% is applied, Landsat can identify vegetation cover changes at an earlier stage. Conversely, when a threshold value greater than 20% is employed, the VIIRS will detect the change 4.5 days earlier than Landsat. Additionally, the VIIRS is capable of detecting changes 25.4 days and 54.8 days faster than Landsat, respectively, when using thresholds of 40% and 70%.

Keywords: change detection; temporal vegetation dynamics; open-area index; multi-temporal VIIRS

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1. Introduction

Tropical forests worldwide have experienced recurrent disturbances over the past few decades, which have adversely impacted biodiversity, hydrology, livelihoods, and the global carbon cycle [1,2]. These disturbances are primarily caused by unsustainable forest exploitation, the expansion of agricultural lands, illegal logging, and forest fires, which alter the structure, composition, and function of forest ecosystems [3]. Some international initiatives have been launched to restore and conserve forest ecosystems, including the

Reducing Emissions from Deforestation and Degradation/REDD+ program [4], the Global Restoration Initiative [5], and the Bonn Challenge [6].

According to the results of COP 16 (paragraph 71 of decision 1/CP.16), the National Forest Monitoring System (NFMS) is an essential component of REDD+ implementation as it provides information on the status and trends of forest resources, land use, and greenhouse gas emissions and removals related to forests. This information enables the measurement, reporting, and verification (MRV) of REDD+ activities and their results, which is essential for accessing results-based payments and ensuring environmental integrity [7]. A comprehensive and dependable system for monitoring forests is essential to offering precise, prompt, and trustworthy information about changes in forest cover to decision-makers. These data can be utilized to prioritize regions for examination and enforcement and to execute policies and measures to prevent, minimize, or restore forest disturbances [8–10].

The importance of NFMS emphasizes the need to develop an early warning system that can effectively address various forest disturbances, including complete deforestation, partial degradation, and a broader loss of vegetation cover, which are collectively referred to as devegetation [11]. It is crucial to acknowledge that devegetation monitoring is part of a broader initiative to preserve and maintain natural resources in a sustainable manner, as well as to mitigate the impacts of environmental degradation [12].

Advances in remote sensing technology enable land scientists to monitor rapid ongoing land cover change with high temporal resolution satellite data [13]. The monitoring of land cover and its seasonal changes continuously in space and time allows for the characterization of vegetation dynamics, and consequently, it should be possible to consider rapid vegetation cover change [14]. In previous studies, the characterization of vegetation dynamics has often been performed using vegetation index values, and the temporal dynamics of these values have been used to detect changes in forest cover and its distribution [15–19].

The application of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data with high temporal resolution has been utilized effectively for real-time forest monitoring in various regions, such as the Brazilian Amazon through the DETER system [20], the State of Mato Grosso's Sistema de Alerta de Desmatamento (SAD) [21], and the FORest Monitoring for Action (FORMA) initiative, which provides a twice-monthly deforestation alerting system for humid tropical regions across Asia, Africa, and Latin America [22]. The research carried out in [23] revealed that MODIS data possess the capacity to deliver consistent information about monthly land cover changes in Indonesia by examining vegetation index patterns.

The development of an early warning system for vegetation cover changes, which utilized Terra-MODIS with a resolution of 500 m, has resulted in the ability to provide information on vegetation changes every 8 days [24]. However, the use of this change detection method in Indonesia's territory is limited by the spatial resolution of the data, particularly in areas such as Java Island, where transient land cover changes may result in a feature size that is less than the minimum detectable extent or complex land cover patterns that affect the threshold value [25]. Despite its limitations in detecting vegetation changes within an area of $\pm$25 ha, the system remains a valuable tool for monitoring vegetation changes in Indonesia due to its ability to provide timely information.

The utilization of MODIS data in the future is likely to be limited to sensors that are more than 24 years old, which is four times their original six-year design life. The Visible–Infrared Imaging Radiometer Suite (VIIRS) sensor, which was launched on the Suomi NPP satellite in 2011, was designed to continue the legacy of MODIS for land observation science [26]. VIIRS data are available at a spatial resolution of 375 m in five spectral bands, and a range of VIIRS data products have been released, including a 500 m surface reflectance product that uses the same grid system as the 500 m MODIS product. Although MODIS records data at a higher resolution of 250 m in the red and NIR bands, one significant improvement of the VIIRS sensor over the MODIS sensor is that it is designed to

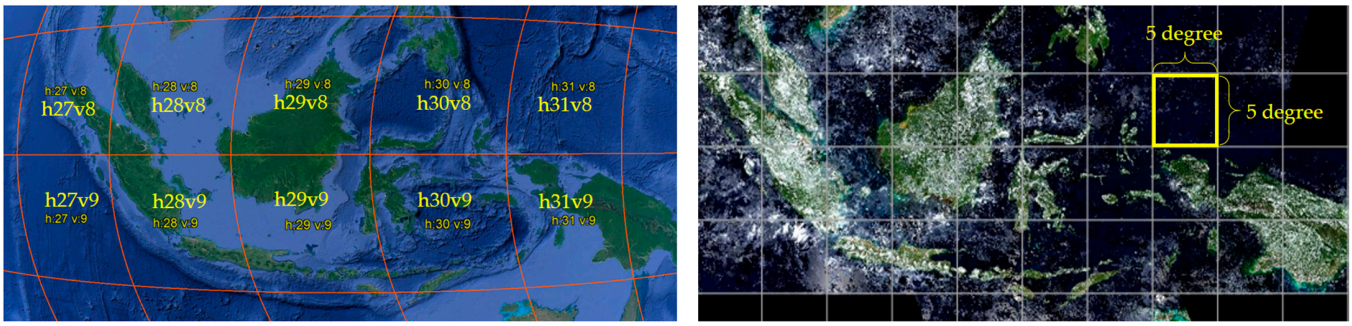
aggregate data from multiple detectors at lower angles of view and delete data from higher angles of view [27].

Considering the anticipated operational use of satellite data for monitoring changes in vegetation cover, which has traditionally been conducted using MODIS data, it is essential to assess the potential performance of VIIRS data for this purpose at a national scale. This study aimed to rigorously evaluate a vegetation cover change algorithm based on VIIRS data to develop a robust early warning system for preventing forest disturbances. The goal was to contribute to more effective forest management and conservation efforts in Indonesia.

2. Materials and Methods

2.1. Satellite Data

A total of 10 Hierarchical Data Format (HDF) tiles of VIIRS data were employed to encompass all areas within Indonesia (Figure 1A). The data were obtained from NASA's Land Processes Distributed Active Archive Center (LP DAAC) and the USGS Earth Resources Observation and Science (EROS) Center through the website https://e4ftl01.cr.usgs.gov/VIIRS/ (accessed on 24 February 2023). In addition to VIIRS data, this study used a combination of specific datasets related to water masking, a list of HDF files for Indonesian regions, and a list of Indonesian 5 × 5-degree tiles. These datasets were utilized to automatically execute the change detection module, following the process design outlined in the Supplementary Materials. The output image was divided into 5 × 5-degree tiles, as shown in Figure 1B.



(A) (B)

Figure 1. (**A**) HDF tile coverage of VIIRS data for all of Indonesia; (**B**) 5 × 5-degree tile of Indonesia.

The VIIRS surface reflectance product, also referred to as VNP09H1, provides an estimation of land surface reflectance derived from data collected by the Suomi National Polar-Orbiting Partnership's (Suomi NPP) VIIRS sensor. It includes information from three imagery bands (I1, I2, I3), which closely correspond to bands 1 (red), 2 (near-infrared/NIR), and 6 (shortwave infrared/SWIR) of the MOD09A1 MODIS product [28,29]. These data are typically available at a resolution of 500 m and are derived through resampling the native 375 m VIIRS resolution in the L2 input product. The VNP09H1 product is archived as an 8-day composite product, comprising the best possible observation for each pixel during an 8-day period, based on high observation coverage, low sensor angle, the absence of clouds or cloud shadow, and aerosol loading [28].

The utilization of mathematical combinations of spectral bands from remote sensing data serves to highlight particular features or characteristics of the Earth's surface, including vegetation, water, and other objects [30]. Both SWIR and NIR bands are commonly used in remote sensing to detect changes in vegetation cover, but they serve slightly different purposes and have varying performance characteristics. NIR is sensitive to changes in vegetation biomass and leaf area index (LAI), making it useful for assessing overall vegetation health and density, while SWIR is valuable for detecting changes in vegetation moisture content and stress.

This study utilized NIR and SWIR to establish the normalized differential open-area index (NDOAI), designed to detect the change in vegetation cover. The mathematical formula for the NDOAI is provided as follows:

$$\text{NDOAI} = \frac{\rho_{\text{SWIR}} - \rho_{\text{NIR}}}{\rho_{\text{SWIR}} + \rho_{\text{NIR}}} \quad (1)$$

where ρ_{SWIR} and ρ_{NIR} represent the reflectance values in the shortwave infrared (SWIR) and near-infrared (NIR) regions of the electromagnetic spectrum, respectively. The SWIR range typically covers wavelengths from approximately 1.0 to 2.5 μm, while the NIR range covers wavelengths from approximately 0.7 to 1.3 μm.

There are several indices that leverage the unique spectral properties of NIR and SWIR bands, such as the Normalized Burn Ratio (NBR), which highlights changes in vegetation cover and moisture content after fire events [31], and the Normalized Difference Water Index (NDWI), which is used to detect the presence of water bodies and monitor changes in water content within vegetation, as it is sensitive to changes in water absorption properties [32,33]. Using both NIR and SWIR bands allows for a complete understanding of vegetation dynamics as well as their modifications in an ecosystem [34].

In a previous study [23], we employed a comprehensive approach by integrating both the normalized differential open-area index (NDOAI) and the normalized difference vegetation index (NDVI). That study meticulously evaluated the effectiveness of these indices in delineating changes in vegetation cover. Upon analysis, we determined that the NDOAI method exhibited superior performance in detecting significant alterations. Hence, in the interest of optimizing efficiency and simplicity in operational procedures for national-scale monitoring endeavors, we exclusively utilized the NDOAI in the present study.

2.2. Image Data Filtering in the Temporal Domain

The VIIRS time series images quickly provide extensive data on vegetation cover changes, serving as an early warning system. However, these time series datasets inevitably face disruptions caused by clouds, atmospheric changes, and aerosol scattering [35]. This interference introduces noise, degrading data quality and creating uncertainty in temporal sequences. This makes it challenging to analyze temporal image sequences due to significant variations in the time series data. Therefore, the initial step in processing data involves addressing these residual noises when using VIIRS time series datasets.

To tackle disturbances, we used VIIRS quality assurance data, specifically the cloud mask product, to eliminate cloudy pixels from VIIRS surface reflectance. Additionally, we employed linear interpolation to estimate values obscured by clouds. Furthermore, to enhance clarity in the time series VIIRS data, we composited VIIRS surface reflectance over an 8-day period to obtain a higher percentage of clear-sky data.

For the NDOAI image data, we employed two filtering techniques. Initially, we utilized linear interpolation to estimate missing values caused by cloud cover, a method that has been widely adopted for filling gaps in VIIRS products, similar to the approach used in [36] for MODIS datasets. Furthermore, we applied a median moving window over three images of the time series to smooth and decrease discontinuities and sharp spikes in the VIIRS data. This approach was previously employed in [37] for the MODIS dataset. Both of filtering approach is illustrated by Figure 2. Applying these filters allows for a clearer definition of the temporal vegetation pattern, which then serves as fundamental information for a near-real-time detection system for vegetation cover changes.

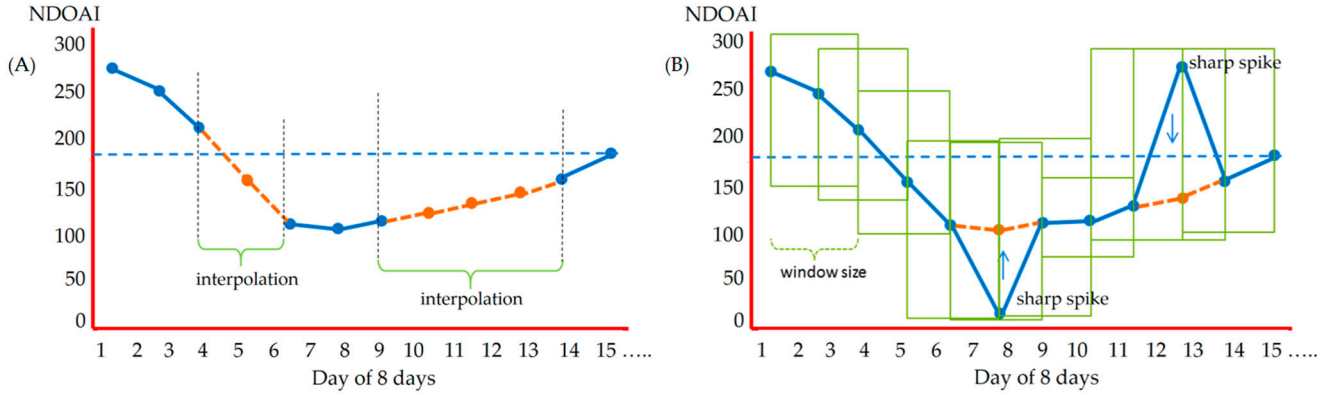


Figure 2. Illustration of filtering procedure by (**A**) linear interpolation to estimate unknown values caused by clouds and (**B**) median moving window over time series datasets (Note: The blue line represents the original NDOI data, the dashed line indicates the filtered NDOAI data, and the green line shows the window size of the filter).

2.3. Vegetation Cover Change Detection

This study identified alterations in vegetation cover by employing an image differencing technique, which involves subtracting pixel values from NDOAI time series data on a pixel-by-pixel basis, with the analysis conducted within a moving window every 8 days. The difference in NDOAI values, denoted as ΔNDOAI, is obtained as follows:

$$\Delta\text{NDOAI} = \text{NDOAI}_{year\ t-1} - \text{NDOAI}_{8\text{-}days\ of\ year} \quad (2)$$

where *year* $t-1$ is the one-year NDOAI data series from the previous period, and 8-*days of year* is the 8-day NDOAI from the current year.

The method used for change detection is a straightforward algorithm developed by the authors of [23] that has been modified to use an 8-day data period instead of the previous 1-month period. This method compares the differences between the vegetation index data from the previous year (year t − 1) and the subsequent 8-day NDOAI values from the current year using a moving window for consecutive analysis (as shown in Figure 3). This approach involves systematically analyzing all new VIIRS data available and has the potential to be operationalized every 8 days to quickly identify vegetation changes across Indonesia.

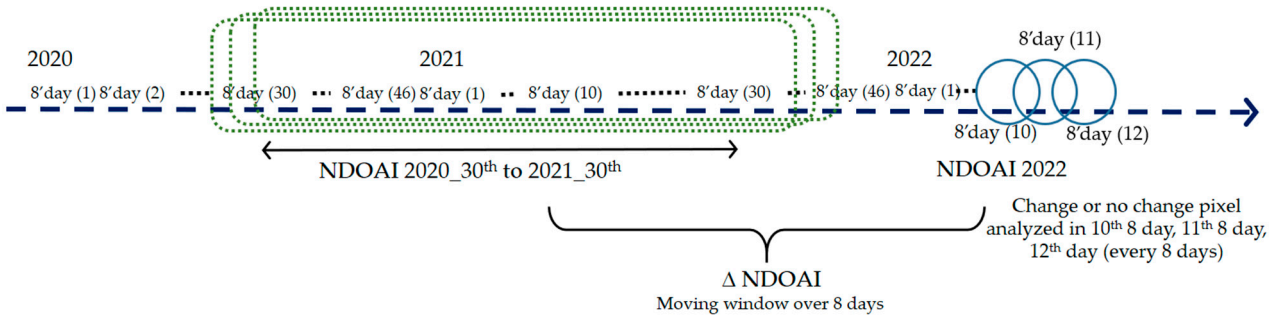


Figure 3. Approach to a simple method for detecting vegetation changes based on differences in NDOAI values within a moving window every 8 days.

The previous study [25] established an NDOAI threshold for detecting changes in vegetation cover. It compared the spatial and temporal pattern similarities between deforestation datasets from MODIS and Landsat-8 OLI satellite imagery, which have different spatial and temporal resolutions. The study conducted a sensitivity and sensibility analysis utilizing probability density functions (PDFs) and cumulative distribution functions (CDFs)

of various geometric features across thresholds ranging from 50 to 130. This analysis, as reported in [25], confirmed that a threshold near 100 was optimal.

Figure 4 provides a visual representation of the shift in the NDOAI value pattern from the datasets of the previous year to the subsequent 8-day data, which are employed to track changes in vegetation cover. Any difference in the value of NDOAI greater than the specified threshold is considered a vegetation cover change, while values below the threshold do not indicate a change in vegetation cover.

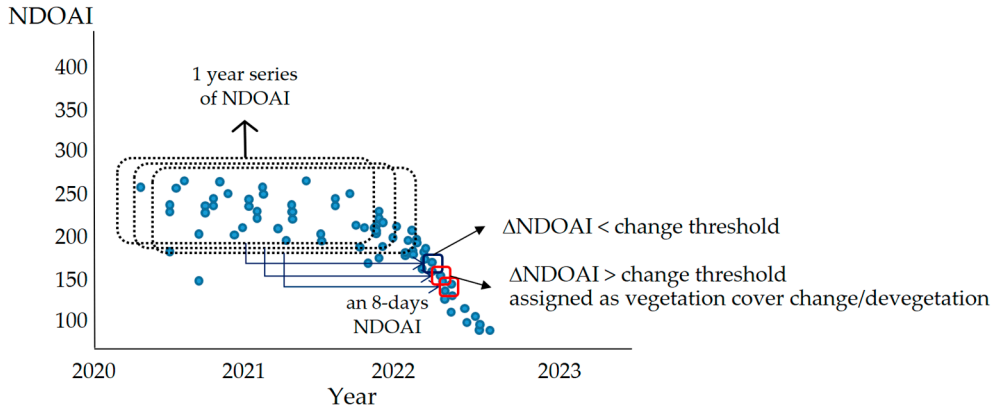


Figure 4. Illustration of the change in the NDOAI value pattern from the previous year's datasets and subsequent 8-day data to detect vegetation cover change every 8 days (Note: The red box indicates that the NDOAI is greater than the change threshold and has been marked as a change).

The change detection system was developed by minimizing the system's interaction with the operator; in other words, it is executed automatically so that information can be conveyed to users quickly. The operational design of Indonesia's early warning system for vegetation cover change detection is available in the Supplementary Materials.

2.4. Accuracy Assessment

2.4.1. Sampling Design for Accuracy Test

A primary concern of the change detection approach is assessing vegetation cover disturbances detected at the subpixel level of the VIIRS. In order to evaluate VIIRS-based vegetation cover changes, we utilized Landsat data with a 30 m spatial resolution. Moreover, to ensure the accuracy of the change detection results in various ecosystems, we referred to more detailed image data, such as SPOT 6/7 and Pleiades satellite data, at several of the selected sites.

Evaluating the level of accuracy at the subpixel level for detecting changes is a complex undertaking in this study, as it involves assessing a change map at a lower resolution than the reference map based on Landsat data. Binary vegetation change maps usually have two clear categories, change and no change, and the same applies to the subsequent accuracy analysis. However, there is a proportion of vegetation disturbance for each VIIRS swath pixel. If no disturbance has occurred within the footprint of a VIIRS observation, it is evident that the observation will be labeled as having no change. Conversely, if 100% of the VIIRS footprint has changed, it will be labeled as vegetation change. Nevertheless, for cases in between, it is somewhat arbitrary to choose a single threshold to separate the two classes.

The evaluation of the real-time detection system's performance was based on a 15.156 reference grid comprising 100 points per grid. Our objective was to accurately identify areas of vegetation disturbance, with a smaller percentage being ideal. To achieve this, we defined the level of vegetation disturbance using various disturbance proportions, such as >70%, >40%, >30%, >20%, and <5%, of a VIIRS pixel size (Figure 5). For instance, a disturbance proportion of >40% indicates that at least 40% of the VIIRS pixel size is disturbed according to the reference map. In this case, VIIRS observations with a proportion greater than 20%

disturbance were classified as "vegetation change", while observations with less than 5% disturbance were categorized as "no change". Observations with a disturbance proportion between 5% and 20% were excluded, as they cannot be clearly labeled as either vegetation change or no change.

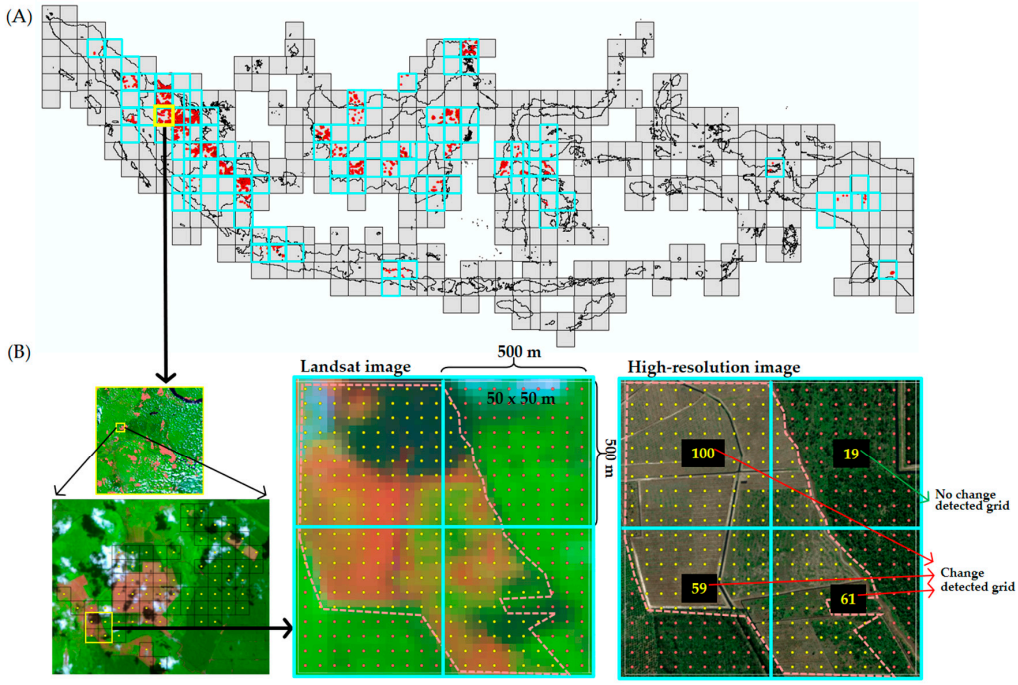


Figure 5. (**A**) The 1 × 1-degree fishnet selected for developing data reference (cyan) and (**B**) VIIRS pixel size overlaid with Landsat ETM+ and a high-resolution image with a 100-point dot grid overlay.

The number of samples for the accuracy test with regard to the percentage of Landsat-based open areas is shown in Figure 6. The figure illustrates a decrease in the amount of data utilized for the accuracy assessment, accompanied by an increase in the open area within a grid size of 500 × 500 m.

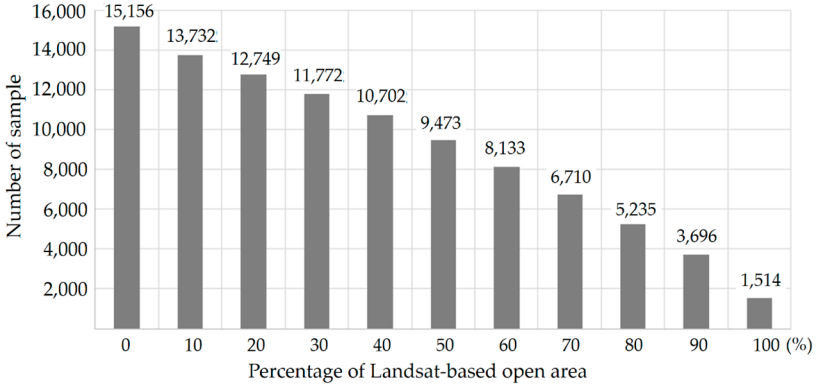


Figure 6. Illustrating the distribution of samples relative to the percentage of Landsat-based open areas.

An accuracy assessment was performed at a 500 × 500 m resolution to determine how the spatial resolution influenced the ability of VIIRS to detect changes and to quantify the minimum size of disturbed patches that we could reliably detect. Even though the optimal threshold may vary with viewing geometry and spatial resolution, only one threshold was applied to detect vegetation disturbance for simplicity.

Moreover, Landsat typically has a 16-day revisit cycle, meaning it captures images of the same location every 16 days. Harmonized periods between the VIIRS and Landsat were

required to assess the temporal accuracy of the system. We converted the VIIRS datasets to a 16-day interval, aiming to align the temporal resolution of the VIIRS data with the Landsat data.

2.4.2. Evaluating Model Performance

In change detection, it is often more critical to ensure that all actual changes are detected (minimizing omission error). Omission errors can lead to a failure to identify genuinely important changes. Producer accuracy measures the extent to which the detection method can recognize the actual changes. This is important for assessing the performance of the change detection method used.

Therefore, to evaluate the results of the comparisons between Landsat's reference data and the change detection method, we computed the following measures for each change detection:

(a) Omission error, which was calculated as the ratio of the number of changed pixels in the ground "truth" polygons that were not identified by the method to the total number of changed pixels in Landsat's reference change bitmap;
(b) Accuracy, which was determined as the ratio of the number of changed pixels in the ground "truth" polygons that were also identified by the method to the total number of changed pixels in Landsat's reference change bitmap.

3. Results

3.1. Vegetation Cover Change in VIIRS Observations

Regarding the near-real-time detection method of vegetation cover change, there are numerous sites that indicate occurrences of devegetation events. The distribution of devegetation in 2022, which was detected by the method, is shown in Figure 7. The utilization of temporal vegetation patterns, as indicated by the NDOAI pattern, enabled the detection of changes in vegetation cover, revealing the specific attributes of these changes, including their location and occurrence every eight days.

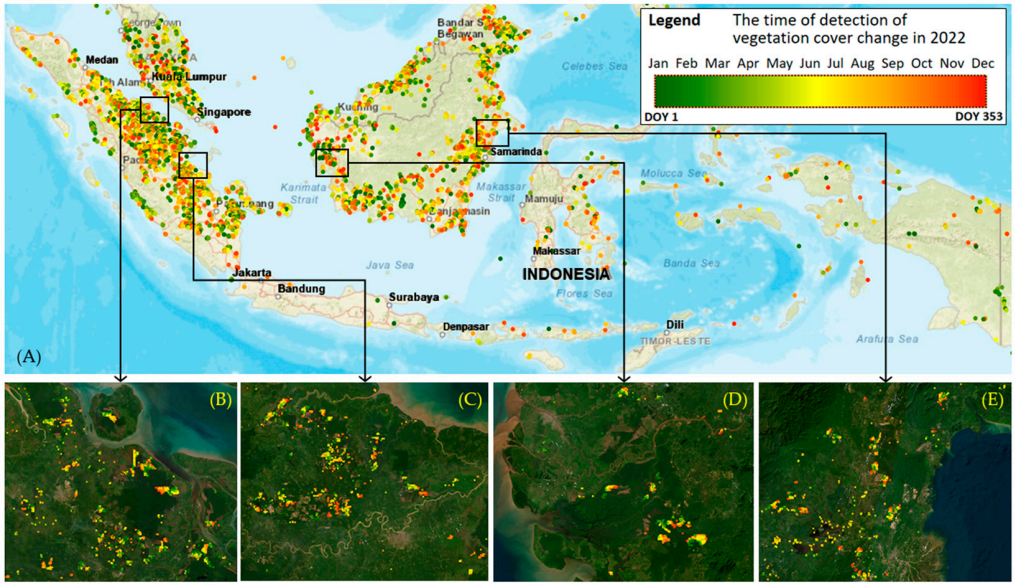


Figure 7. Distribution of vegetation cover change during 2022 detected by the devegetation method: (**A**) all regions of Indonesia, and selected sites in (**B**) Riau, (**C**) Jambi, (**D**) West Kalimantan and (**E**) East Kalimantan.

3.2. Spatial Accuracy of the Change Detection Results

There is often a trade-off between accuracy and sensitivity in change detection. A threshold that is too low may result in false positives, while a threshold that is too high

may lead to missed changes. Striking the right balance is essential for achieving optimal spatial accuracy in capturing meaningful changes over time.

Figure 8 presents the results of the 8-day devegetation analysis conducted using VIIRS and Landsat data in the year 2022, revealing a similarity between the two datasets. The comparable outcomes underscore the reliability and consistency of the VIIRS in capturing and characterizing vegetation cover changes over short temporal intervals compared to the medium resolution of Landsat.

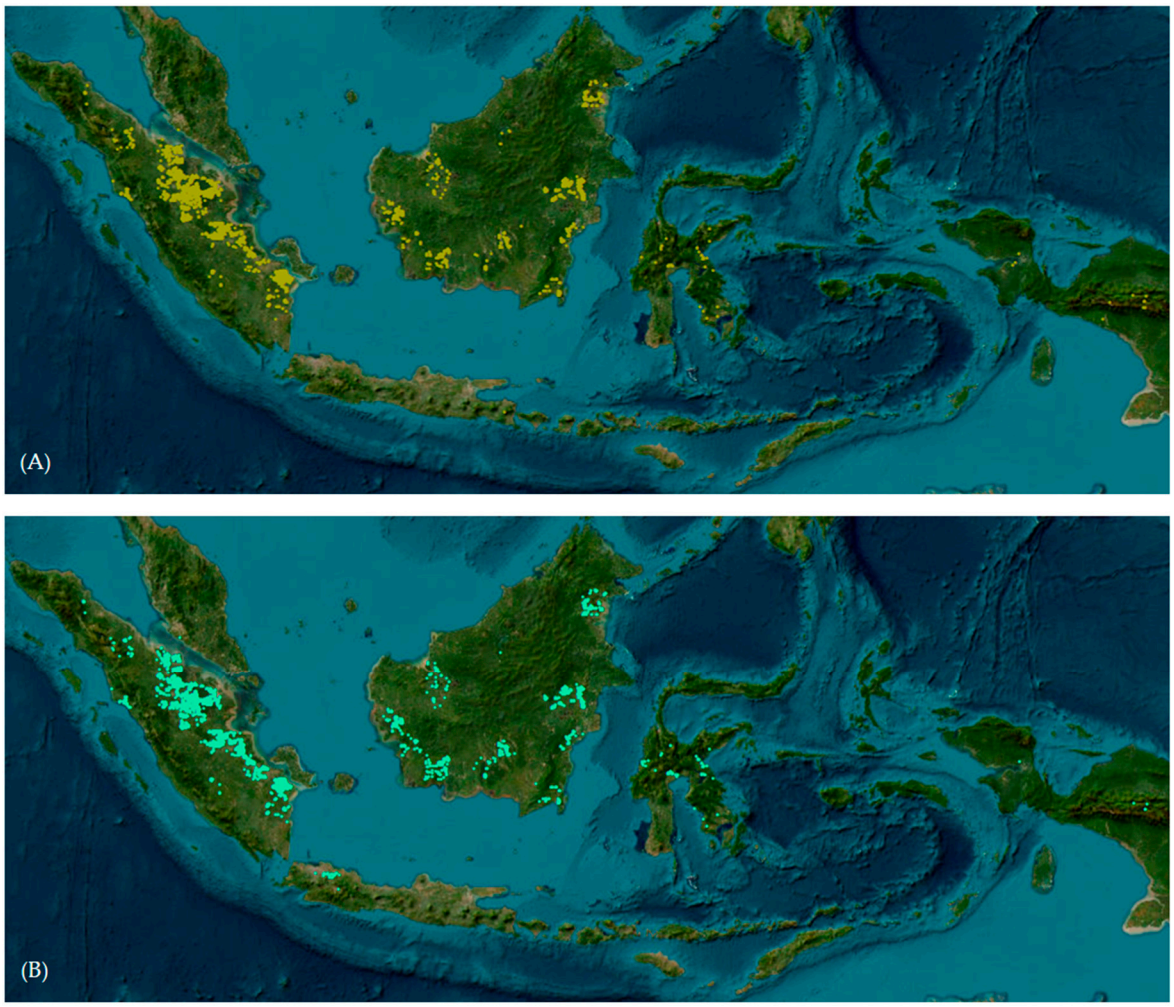


Figure 8. The result of the devegetation analysis conducted in the year 2022 using (**A**) VIIRS and (**B**) Landsat.

The results of the comparison between the vegetation cover changes depicted in Figure 9, which were derived from the examination of VIIRS and Landsat data, correspond to the outcomes of the area analysis.

In pursuit of the overarching goal of identifying changes in vegetation cover at an early stage, a threshold of 20% of the open area in a 500 × 500 m grid was used to assess the accuracy of the VIIRS-based vegetation cover change. This approach is rooted in the understanding that resources can be optimized without compromising the accuracy of the detection process by focusing on representative changes over a total area of 500 × 500 m (25 ha).

Table 1 displays the results of an accuracy assessment based on different threshold values for Landsat-based open areas. The thresholds represent the percentage of open areas considered for the accuracy assessment of the method used to detect a vegetation cover change in 500 × 500 m of VIIRS data.

Table 1. Accuracy assessment results with Landsat-based open area in a 500 × 500 m grid.

Percentage of Open Area (Set as the Threshold)	Number of Samples	Omission Err.	Accuracy
~5%	15,156	31.80%	68.20%
20%	12,749	26.33%	73.67%
30%	11,772	24.69%	75.31%
40%	10,702	22.98%	77.02%
50%	9473	21.00%	79.00%
70%	5844	17.30%	82.70%

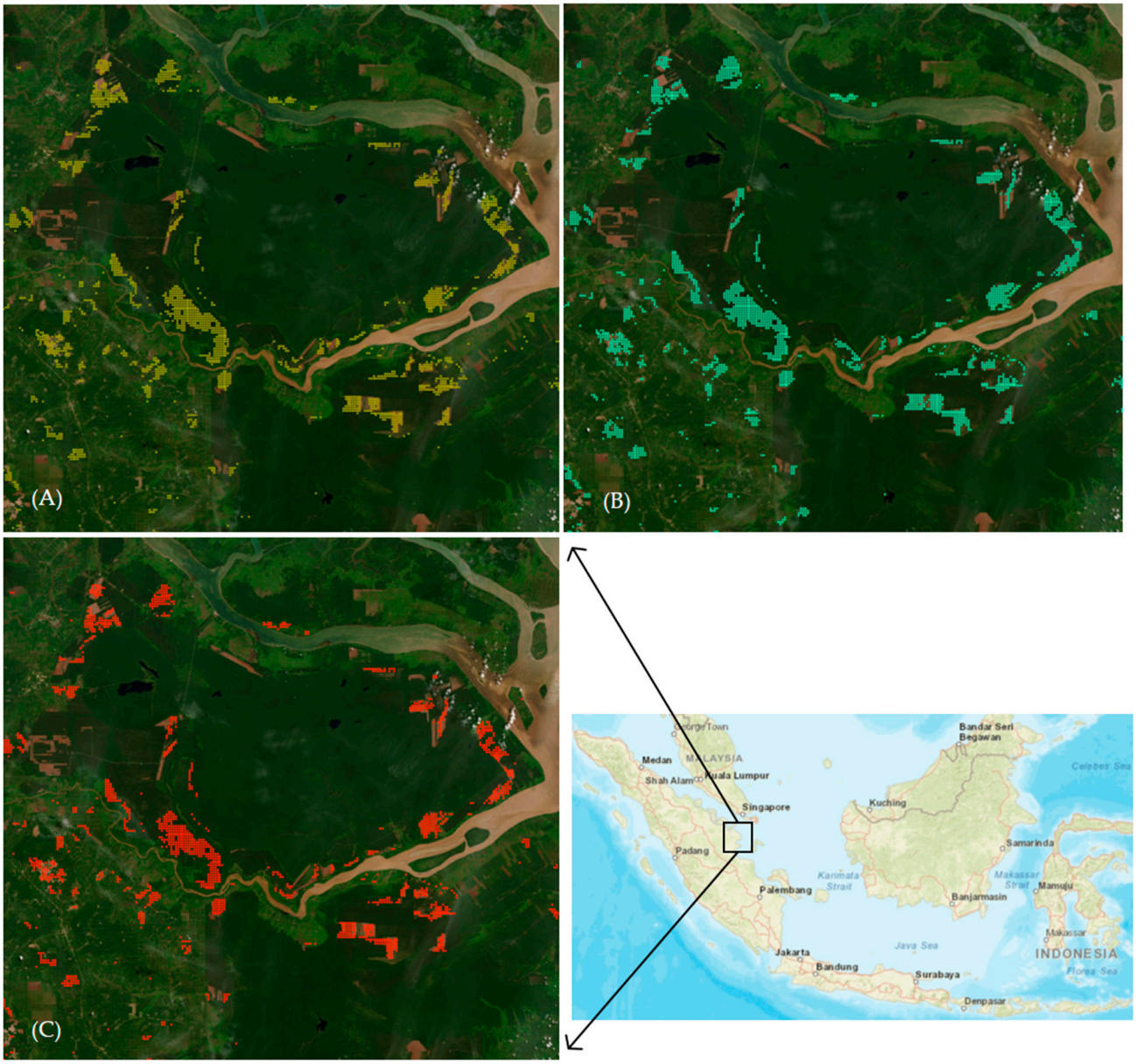


Figure 9. Comparison of devegetation analysis results based on (**A**) VIIRS, (**B**) Landsat, and (**C**) a combination of both for the selected site in Riau, Sumatra.

Table 1 shows that the accuracy of the system increased progressively with higher thresholds. For instance, at the lowest threshold of 5%, the accuracy was 68.20%, while at 70%, the system achieved its peak accuracy of 82.70%. This trend indicates that, in general,

increasing the threshold percentage is associated with an improvement in accuracy. Higher thresholds lead to more selective change identification, potentially reducing false positives and enhancing overall accuracy in the system's analysis.

3.3. Temporal Accuracy of the Change Detection Results

The use of high-temporal-resolution satellite data is crucial for monitoring rapid changes and short-term events, such as wildfires, deforestation, and urban development. However, the accuracy of change detection results in near-real-time systems is a critical issue. The temporal accuracy of change detection results represents the system's ability to accurately capture and represent changes over time.

The devegetation analysis based on data from both the VIIRS and Landsat satellite imagery demonstrates a high degree of spatial similarity in the results obtained. However, there are notable differences in the time periods during which the changes are detected, as shown in Figure 10.

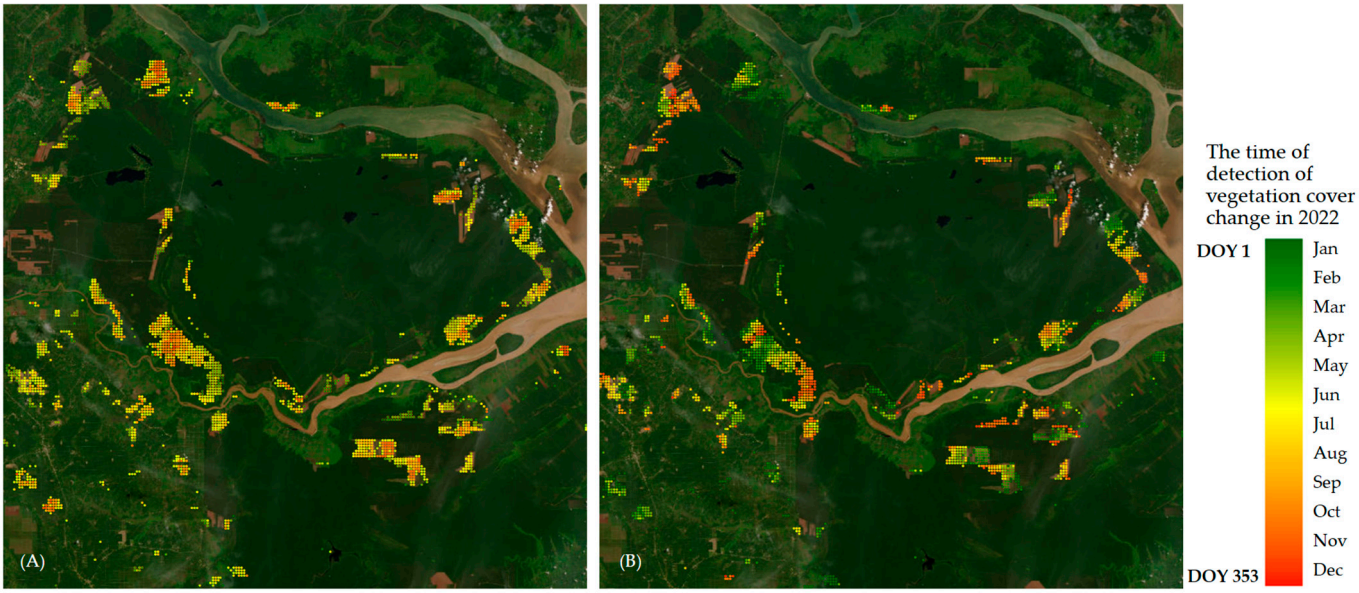


Figure 10. A temporal comparison of the 16-day devegetation analysis results for the selected site in Riau, Sumatra, based on (**A**) VIIRS and (**B**) Landsat data.

A threshold in a change detection algorithm plays a pivotal role in determining what is considered a significant change. A lower threshold might lead to the detection of smaller changes, potentially enhancing the temporal precision of the algorithm. Conversely, a higher threshold may filter out smaller variations, emphasizing more substantial alterations and potentially reducing temporal precision.

Figure 11 provides specific numerical insights into the detection speed difference between VIIRS and Landsat using different levels of thresholds. If a threshold value of less than 20% is applied, Landsat will identify devegetation at an earlier stage. Specifically, a 5% open area, equivalent to 1.25 hectares, will be detected 20.2 days sooner than by the VIIRS (−1.26), and a 10% open area, corresponding to 2.5 hectares, will be identified 11.8 days ahead of the VIIRS (0.74).

Meanwhile, when a threshold value greater than 20% is employed, the VIIRS will identify devegetation 4.5 days earlier compared to Landsat. Furthermore, with 40% open area (10 hectares) and 70% open area (18.75 hectares), the VIIRS is capable of detecting the change 25.4 days and 54.8 days faster than Landsat, respectively.

The thresholds in each region represent variations, as demonstrated by the different time periods in which changed areas can be detected. The Sumatra and Kalimantan regions show that the VIIRS can detect changes more rapidly than Landsat-based systems when

the threshold is set at 20% of the total open area (Figure 12). However, other regions like Sulawesi and Papua present challenges in identifying patterns, as the detected change areas are limited in these areas. The optimal threshold may vary depending on the specific characteristics of the data, the type of changes being monitored, and the desired level of accuracy. Therefore, considering the context and adjusting the threshold accordingly are crucial for achieving the best temporal accuracy in change detection.

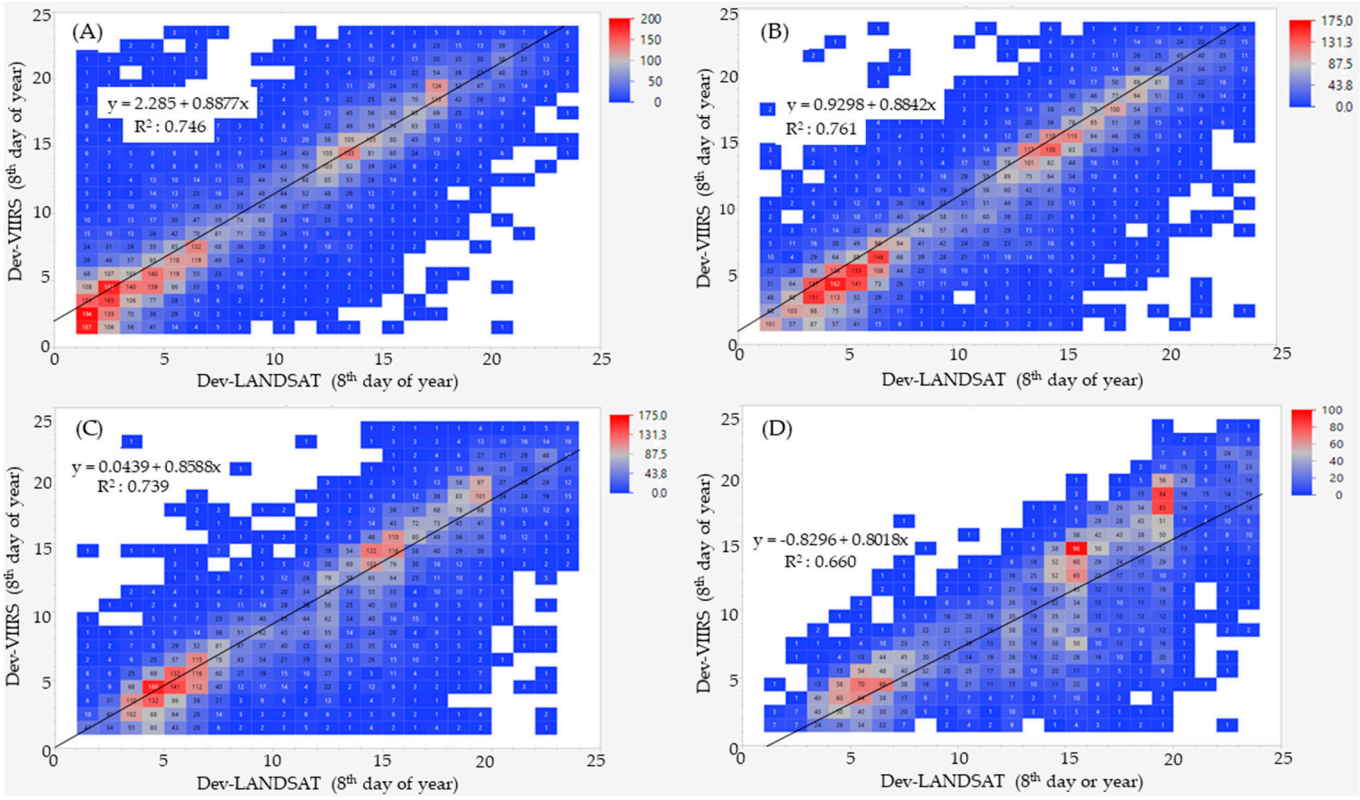


Figure 11. The disparity in detection speed between VIIRS and Landsat using different levels of thresholds as a reference point: (**A**) 5%, (**B**) 20%, (**C**) 40%, and (**D**) 70%.

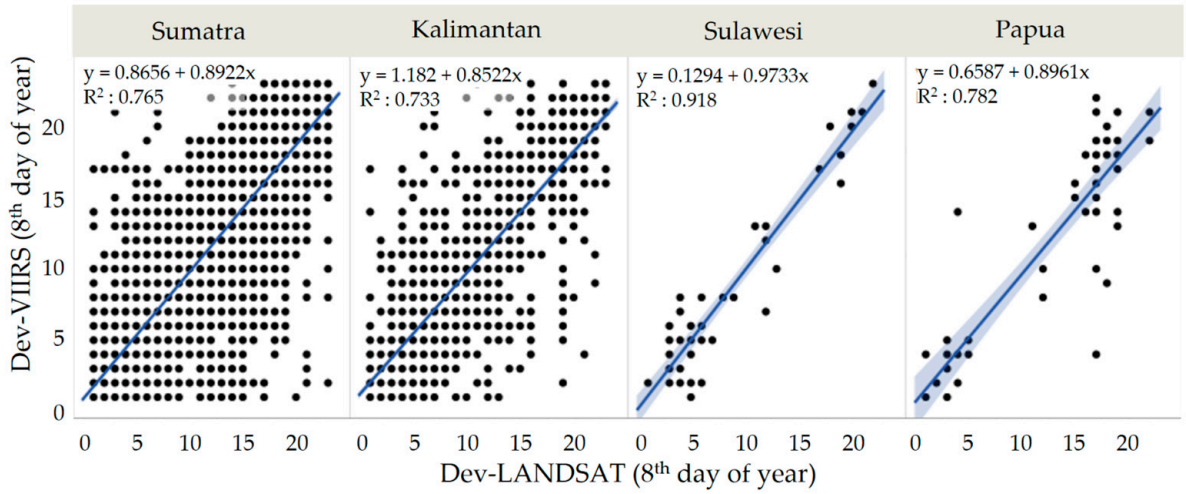


Figure 12. A comparison of different time frames between VIIRS and Landsat-based datasets, highlighting alterations in specific regions identifiable through the application of a 20% threshold.

4. Discussion

4.1. Minimum Detectable Patch Size

The effectiveness of a change detection method can be evaluated by determining the minimum detectable patch size, which is a critical metric. Establishing a standard requirement for this factor is challenging due to the diverse types and sizes of vegetation disturbances. The coarse spatial resolution of VIIRS data presents challenges in characterizing vegetation disturbances on a per-pixel basis. Typically, the minimum detectable patch sizes reported in MODIS-based change detection systems [20,38,39] range from 15 to 50 ha. While the use of VIIRS-based systems remains limited, it is worth noting that similar moderate-resolution satellites, such as MODIS, have been extensively utilized as a benchmark for assessing VIIRS performance. This is important to note since the average patch size of vegetation disturbances in tropical regions often includes small-scale disturbances that are less than 10 ha. As a result, a change detection system operating at a minimum scale of 15 to 50 ha may underestimate the extent of human-induced vegetation disturbances.

Utilizing a higher threshold value results in a larger area of detected change, which can impact the accuracy of the algorithm. Establishing a threshold of 2.5 ha (10% of the 500 $\times$ 500 m VIIRS grid size) enabled the algorithm to correctly identify 90.78% of the altered regions, although its accuracy was only 69.5%. On the other hand, employing a threshold of 5 ha (20%) allowed the algorithm to detect 86% of the changed regions, while maintaining an accuracy of 73.7%. It is worth noting that the algorithm achieved an accuracy of over 80% when using a threshold of 12.5 ha for identifying altered areas.

The accuracy of the system is closely linked to both the number of samples and the threshold utilized. The greater the diversity and quantity of samples, the more precisely the accuracy of the system can be gauged, offering a more comprehensive insight into its performance across a range of scenarios. At the same time, the chosen threshold has a significant impact on the precision of the system, as different thresholds can lead to varying results in identifying alterations. Locating an appropriate equilibrium between a sufficient number of representative samples and an optimal threshold is essential for achieving accurate and reliable outcomes in the analysis and detection abilities of the system, as demonstrated in Figure 13.

It is crucial to acknowledge that the detected disturbed area can differ across regions. For instance, in Sumatra, the minimum detectable size was observed to be 8.68 ha, while in Kalimantan, it was 5.98 ha. Sulawesi exhibited a minimum detectable size of 4.44 ha, and in Papua, it was 7.33 ha. This regional variation highlights the impact of geographical characteristics on both the accuracy and the detected change areas.

An effective change detection system that acquires daily images and can identify disruptions at the VIIRS pixel or subpixel level can significantly improve the monitoring of vegetation cover disturbances. The technique described in this paper allows for the per-pixel detection of vegetation disturbances based on VIIRS data, matching predicted and observed images precisely in terms of footprints and sensor responses. However, the small number of patches was not enough to determine the minimal detectable patch size with certainty. Additionally, the study was limited to Java, Sulawesi, and Papua, which further reduced the reliability of the results. To determine the smallest detectable area of disturbance, a more extensive accuracy assessment, involving a larger sample size and covering broader geographic regions, is necessary.

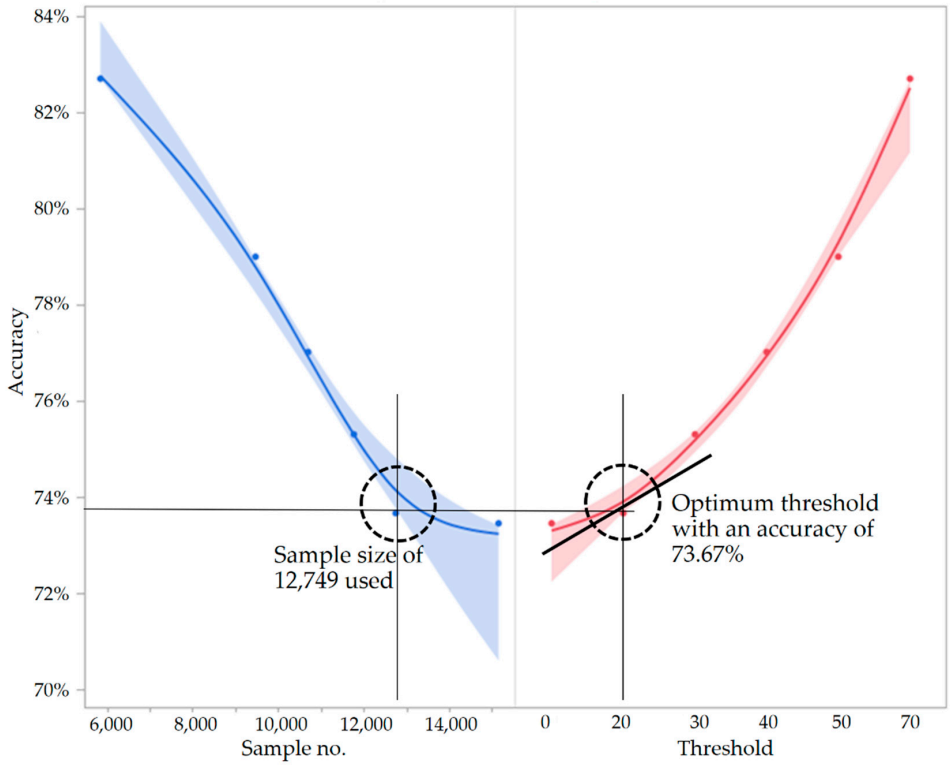


Figure 13. The relationship between accuracy, sample quantity, and the thresholds.

4.2. Near-Real-Time Monitoring

VIIRS imagery and associated products provide almost daily coverage of Indonesia, revolutionizing the study and observation of the Earth. This paper presents research on the potential performance of VIIRS data in facilitating the near-real-time monitoring of vegetation disturbances. The methodology involved using Landsat time series images, which served as a main reference for spatiotemporal comparison with the VIIRS-based analysis results.

Figure 14 shows that there is a significant difference in detection speed between the VIIRS and Landsat when more than a 40% threshold (>10 ha) or less than a 5% (<5 ha) threshold of open areas within a 500 × 500 m grid size is used. The data show an average time gap of 4.45 days (0.28) indicating a consistent pattern when using a 20% threshold. However, it is important to note that there is a considerable range of variation, with a deviation of 48 days (3.0), which highlights the impact of the chosen threshold on the temporal accuracy of and variability in the detection speed between these two datasets.

The image differencing approach is nearly ideal for national-scale monitoring due to its simplicity and efficiency, which are crucial for processing large datasets across extensive regions. This method involves subtracting one image from another to highlight changes in vegetation cover, making it straightforward to implement and computationally less intensive compared to more complex techniques. Its simplicity allows for rapid analysis and timely results, which are essential for large-scale environmental monitoring. Using the approach, we attempted to identify areas of vegetation disturbance of 5 ha or larger in Indonesia every two weeks based on VIIRS data.

In comparison, remote sensing technologies like machine learning offer advanced capabilities for change detection but come with increased complexity and computational demands. Machine learning algorithms can handle a variety of data types and can be trained to recognize subtle patterns and changes in vegetation cover, potentially providing more accurate and detailed results [40,41]. However, these methods require substantial computational resources, expertise in algorithm training and validation, and extensive labeled datasets for training.

While machine learning techniques excel in accuracy and detail, their complexity and resource requirements can be a drawback for national-scale monitoring where quick, efficient processing is needed. In contrast, the image differencing approach, with its ease of use and lower computational demands, is more practical for large-scale applications where the primary goal is to achieve rapid and broad monitoring coverage.

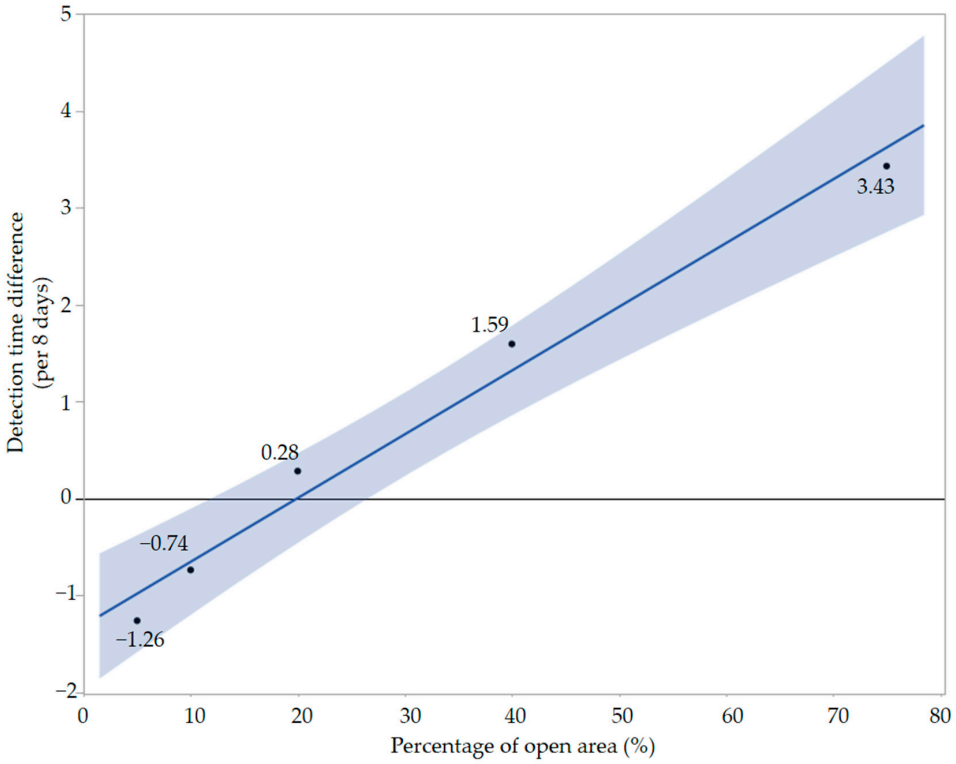


Figure 14. Temporal discrepancy in detection time between VIIRS and Landsat based on the threshold level set by the percentage of open area within a 500 × 500 m grid size.

4.3. Future Improvement

This study aimed to precisely match the observed VIIRS and Landsat images, using careful consideration. Although a basic image differencing algorithm showed promising results in subsequent change detection, it still requires refinements to improve its performance, especially for developing an operational monitoring system to be implemented on a national scale. The simplicity of the image differencing approach in the NDOAI algorithm makes it almost ideal for national-scale monitoring, as a straightforward and efficient method is crucial for processing large datasets across extensive regions.

To achieve a reliable national-scale monitoring system, it is crucial to address the limitations posed by seasonal variability, especially in arid areas like the southeastern part of Indonesia, where long-term monitoring over at least one year is required for accurate results. For instance, a high NDOAI can resemble a high normalized difference built-up index (NDBI), indicating urban or built-up areas [42], while a low NDOAI can be mistaken for a low normalized difference water index (NDWI), which signifies low levels of vegetation moisture [43]. The diverse vegetation types and varying environmental conditions across Indonesia add further complexity, as the NDOAI may respond differently depending on the local vegetation structure and phenological stages, making consistent interpretation challenging. Future research should focus on enhancing the algorithm by integrating more sophisticated techniques, such as machine learning-based methods, which can adaptively learn optimal thresholds and improve the robustness of change detection across various landscapes and conditions.

Obtaining accurate predictions of Landsat images for a specific day is essential, as it serves as the reference data for assessing the results of VIIRS-based change detection. Accurate predictions depend on the availability of Landsat images, and cloud cover can reduce the availability of useful images. Future studies should explore advanced cloud removal and image interpolation techniques to mitigate the impact of cloud cover and enhance the temporal and spatial resolution of the dataset.

A significant portion of the omission errors identified in the accuracy assessment were related to areas where vegetation disturbances had occurred before the study period. As the predicted time series was based on one year of observations preceding the study period, the time series model incorrectly classified these regions as intact forests, resulting in commission errors when comparing predictions to actual observations. Future iterations of the fusion method will use an updated algorithm, which is expected to reduce the number of commission errors. Additionally, incorporating longer time series data and integrating ancillary data sources, such as historical disturbance records and land use maps, could improve the accuracy of the predictions.

Moreover, it is essential to evaluate the method in Java to comprehensively assess the minimum detectable patch size and near-real-time performance. Future research should conduct extensive field validation and apply the method to diverse geographic regions to test its scalability and reliability. Implementing automated, near-real-time monitoring systems using the refined algorithm could significantly enhance environmental monitoring and management practices, providing timely and accurate information for decision-making and policy development.

5. Conclusions

This study indicated that increasing the threshold percentage corresponds with enhanced accuracy. In change detection, there is typically a trade-off between precision and sensitivity. A threshold that is set too low may result in false positives, while a threshold that is set too high may lead to missed changes. The accuracy assessment results revealed a consistent pattern: as the threshold percentage of open areas increases, the system's accuracy improves progressively. Lower thresholds are associated with lower accuracy rates, while higher thresholds yield higher accuracy, with the optimal level attained at 82.70% at a threshold of 70%. Nonetheless, it is noteworthy that the optimal equilibrium between resource utilization and accuracy is achieved at a threshold of 20%, where the system attains an accuracy of 73%. The 20% change in the VIIRS pixel size that can be detected is sufficient for use as a near-real-time system on a national scale in Indonesia.

This research demonstrates that applying a threshold value of less than 20% with Landsat can enable the identification of vegetation cover changes at an earlier stage. Conversely, employing a threshold value greater than 20% with the VIIRS will result in identifying changes 4.5 days earlier than Landsat. Furthermore, the VIIRS is capable of detecting changes 25.4 days and 54.8 days faster than Landsat, respectively, when using thresholds of 40% and 70%.

6. Patents

Simple Patent Registration No: S00202211691 entitle "Vegetation Cover Change Rapid Detection System Based on Optical Satellite Imagery Data".

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16111958/s1, Figure S1: Diagram of the process of developing the early warning system for changes in vegetation cover based on VIIRS image data; Figure S2: Module and data flow design for developing the early warning system for detecting changes in vegetation cover based on VIIRS image data; Figure S3: Results of identification of changes in vegetation cover data per 8 days using VIIRS data.

Author Contributions: The study was conceptualized by Y.S. and K.K., with the methodology developed by Y.S., K.K. and S.A.H. The software was implemented by S.A.H. and K.K. Validation

was performed by T.K., A.T. and K.K. Formal analysis was carried out by N.I. Investigation and resource acquisition were performed by R.R., J.P. and A.B.U. Data curation was managed by R.R. and Y.S. The original manuscript was prepared by Y.S., with subsequent review and editing conducted by the same author. Visualization of the data was performed by Y.S. Supervision of the project was provided by L.B.P. and B.A.M. Project administration was handled by Y.S. and S.A.H. Funding for the research was acquired by B.A.M., L.B.P. and Y.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data for devegetation are accessible at https://nfms.menlhk.go.id/ (accessed on 14 December 2023). Additionally, the algorithm we created for this study, which is based on an open-source platform, can be obtained by contacting the corresponding author upon request.

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