SATELLITE IMAGE ANALYSIS USING AI FOR DEFORESTATION MONITORING IN KALIMANTAN AND SUMATERA

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Abstract

Deforestation in Indonesia, particularly in Kalimantan and Sumatra, remains a significant environmental issue with broad impacts on global ecosystems. This study aims to analyze forest cover change using satellite imagery combined with Artificial Intelligence (AI) technology. The data consist of Landsat 8 and Sentinel-2 imagery from 2015 to 2024. The main methods applied are Convolutional Neural Network (CNN) and Random Forest for classifying forest and non-forest areas. The results show that the model achieved an accuracy rate of 92.4% with a Kappa coefficient of 0.89. Central Kalimantan and South Sumatra recorded the highest deforestation rates, mainly driven by oil palm expansion and mining activities. The integration of satellite imagery and AI has proven effective for early warning systems of deforestation and supports evidence-based conservation policy planning.

Keywords: Deforestation, Kalimantan, Sumatra, Satellite, AI.

INTRODUCTION

Deforestation is one of the most serious global environmental issues, with wide-ranging impacts on ecosystem balance, climate change, and biodiversity. Indonesia, as one of the countries with the largest tropical forests in the world, plays a crucial role in maintaining global climate stability. However, the rate of forest cover loss in Indonesia—particularly on the islands of Kalimantan and Sumatra—remains relatively high due to plantation expansion, illegal logging, and land-use conversion (Margono et al., 2014; Gaveau et al., 2021). Deforestation in these two islands has led to environmental degradation, increased carbon emissions, and the loss of habitats for endemic flora and fauna.

Monitoring deforestation is a strategic step in supporting sustainable forest management policies. One of the most widely used technologies for this purpose is remote sensing, which enables periodic and large-scale monitoring of land cover changes through satellite image analysis (Hansen et al., 2013). Satellite imagery such as Landsat, Sentinel, and MODIS provides multispectral data that can be used to detect vegetation changes and forest degradation with high spatial accuracy (Zhang et al., 2020).

In recent years, advances in Artificial Intelligence (AI), particularly machine learning and deep learning, have revolutionized the analysis of satellite imagery. AI-based approaches are capable of improving the accuracy of land cover classification and forest change detection while offering more efficient processing times compared to conventional methods (Li et al., 2022). AI models such as Convolutional Neural Networks (CNN) and Random Forest have been successfully applied to identify deforestation patterns and predict areas at high risk of forest loss (Pham et al., 2021).

The integration of satellite imagery and artificial intelligence opens significant opportunities for automated, rapid, and accurate deforestation monitoring. The implementation of this technology is expected to support governments and conservation agencies in developing data-driven policies for forest preservation. In Indonesia, AI- and geo-intelligence–based systems have begun to be adopted for forest and land fire monitoring, including by the Ministry of Environment and Forestry (MoEF) in collaboration with various international institutions (Ministry of Environment and Forestry, 2023).

Based on this background, this study aims to analyze the use of AI-based satellite imagery for monitoring deforestation in Kalimantan and Sumatra. The research focuses on the application of AI algorithms to identify changes in forest cover,

determine the spatial patterns of deforestation, and evaluate the effectiveness of these methods in supporting decision-making for sustainable forest management. Previous studies have used satellite pictures and Artificial Intelligence for watching over forests in some parts of Indonesia. We do not have many studies that compare the forests in Kalimantan and Sumatra. Most studies only look at one way of using Artificial Intelligence, which makes it hard to know what method is best. This study is important because it looks at different Artificial Intelligence methods and checks what is happening to the forests in Kalimantan and Sumatra. These two places are losing a lot of forest. It is good to understand what is going on with the forests, in these areas. Artificial Intelligence can help us do that.

LITERATURE REVIEW

1. Deforestation and Its Impacts

Deforestation is the process of permanent loss of forest cover caused by human activities or natural factors. In Indonesia, the rate of deforestation remains high, particularly on the islands of Kalimantan and Sumatra, largely due to the conversion of forests into oil palm plantations, logging activities, and infrastructure development (Margono et al., 2014). The impacts of deforestation extend beyond biodiversity loss to include increased greenhouse gas emissions and disruption of the hydrological cycle (Gaveau et al., 2021). Furthermore, the loss of primary forests in these regions exacerbates the risk of ecological disasters such as floods and landslides and accelerates regional climate change (Austin et al., 2019).

2. Utilization of Satellite Imagery in Forest Monitoring

Remote sensing technology has become a primary tool for monitoring land cover changes and deforestation on a periodic basis. Satellite imagery such as Landsat, Sentinel-2, and MODIS provides multispectral data with sufficient spatial and temporal resolution to detect vegetation changes (Hansen et al., 2013). Through vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), researchers can identify reductions in vegetation density that indicate deforestation (Zhang et al., 2020).
In addition, radar imagery such as Sentinel-1 can provide more accurate information in tropical regions with high cloud cover, such as Kalimantan and Sumatra (Reiche et al., 2016). The integration of optical and radar data further enhances the accuracy of forest cover change detection.

3. The Role of Artificial Intelligence (AI) in Satellite Image Analysis

Artificial intelligence (AI) has transformed the paradigm of satellite image analysis from manual approaches to automated and adaptive systems. Machine learning–based methods such as Random Forest (RF), Support Vector Machine (SVM), and k-Nearest Neighbors (kNN) are widely used for land cover classification (Li et al., 2022). Meanwhile, deep learning approaches using Convolutional Neural Network (CNN) architectures have proven superior in detecting complex spatial patterns that are difficult to identify using conventional methods (Pham et al., 2021).
Several studies have shown that CNN models can identify deforestation areas with accuracy exceeding 90%, particularly when applied to high-resolution imagery such as Sentinel-2 and PlanetScope (Zhu et al., 2022). Moreover, AI-based time-series analysis approaches enable early detection of deforestation activities before major changes occur (Sun et al., 2020).

4. Related Studies in Indonesia

In Indonesia, numerous studies have integrated remote sensing data and AI for forest monitoring. For example, the Ministry of Environment and Forestry (MoEF) has begun adopting GeoAI-based systems to monitor forest cover changes and detect forest fires in real time (Ministry of Environment and Forestry, 2023). Research by Herdiansyah et al. (2022) also demonstrated that the combination of Landsat-8 data and the Random Forest algorithm can map deforestation in Central Kalimantan with very high accuracy.
Similar studies in Sumatra indicate that deep learning models are able to distinguish natural forests, plantations, and deforested areas more precisely than vegetation index–based methods (Sari & Nugroho, 2021). These studies highlight the importance of AI utilization in Indonesia's forest monitoring systems toward sustainable and scientifically based forest management.

5. Research Gap

Although many studies have examined the use of satellite imagery to detect deforestation, most are regional in scope and have not integrated analyses across both Kalimantan and Sumatra. In addition, many studies focus on a single algorithm without comparing the effectiveness of different AI methods. Therefore, this research is important to address these gaps by analyzing the performance of various AI models in detecting deforestation across the two main regions contributing to the largest forest loss in Indonesia.

Satellite images are really good at showing changes in the land. They have been used for a time to do this. Computer programs, like the ones that use something called Artificial Intelligence have made it easier to tell what is what in these images.

The problem is that people do not agree on which computer program is best for looking at areas of forest that have been cut down. Some people think that one kind of program called a CNN model is really good at recognizing patterns in pictures.

Other people think that different programs, like Random Forest and SVM algorithms are better for looking at kinds of pictures that have many colors.

We need to try different computer programs to see which one is best for looking at forests in a big country, like Indonesia. Satellite imagery and Artificial Intelligence can be used together to do this.

Artificial Intelligence and satellite imagery can help us understand what is happening in these forests.

RESEARCH METHODOLOGY

1. Research Approach

This study employs a descriptive quantitative approach using spatial analysis methods based on satellite imagery combined with Artificial Intelligence (AI) algorithms. The primary objective of the research is to identify, classify, and map changes in forest cover (deforestation) in the regions of Kalimantan and Sumatra over a specific time period using medium-resolution satellite imagery data.
This approach was selected because it provides an objective depiction of deforestation dynamics and enables predictive analysis of areas potentially at risk of forest cover loss in the future (Pham et al., 2021).

2. Study Area and Period

The study area includes two major islands in Indonesia, namely Kalimantan and Sumatra, which are regions with the highest deforestation rates in Southeast Asia (Margono et al., 2014). Spatially, the research covers all provinces on both islands, including conservation forests, production forests, and other land-use areas.
This study utilizes time-series data covering the period from 2013 to 2023, with a focus on forest cover changes over the past decade. Data processing and analysis were conducted in 2025 using open-source software such as Google Earth Engine (GEE) and a Python computing environment.

3. Data and Data Sources

The primary data used in this study consist of multispectral and radar satellite imagery obtained from the following sources:

Table 1. Satellite Image Data

Data Type	Source	Spatial Resolution	Temporal Resolution	Function
Landsat 8 OLI/TIRS	USGS/NASA	30 meters	16 days	Forest cover analysis and vegetation change detection
Sentinel-2 MSI	ESA	10 meters	5 days	Detailed land cover change classification
Sentinel-1 SAR	ESA	10 meters	12 days	Detection of deforestation under cloud cover

Data Type	Source	Spatial Resolution	Temporal Resolution	Function
MODIS Vegetation Index	NASA	250 meters	Daily	NDVI trend and vegetation anomaly analysis

In addition to satellite imagery, secondary data were used, including administrative boundary maps (Geospatial Information Agency/BIG), forest area data (Ministry of Environment and Forestry/KLHK), and fire hotspot data (NASA FIRMS) for validation of detection results.

4. Research Stages

a. Data Pre-processing

This stage includes radiometric and atmospheric correction, study area clipping, and cloud masking to remove cloud cover interference (Zhu & Woodcock, 2012). All processes were conducted within the Google Earth Engine (GEE) environment using the Fmask algorithm and QA band filtering.

b. Vegetation Index Extraction

Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) were calculated to assess vegetation density and detect forest degradation. The NDVI formula is expressed as follows (Huete et al., 2002):

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)}$$

A significant decline in NDVI values over a certain period indicates the occurrence of deforestation.

c. Application of Artificial Intelligence Models

At this stage, several AI algorithms were applied for land cover classification and forest change detection, including:

- **Random Forest (RF)** – for multi-class classification based on spectral values and vegetation indices.
- **Convolutional Neural Network (CNN)** – for spatial pattern analysis using high-resolution imagery.
- **Support Vector Machine (SVM)** – to compare classification performance with non-neural models.

The datasets were trained using training samples derived from visual interpretation and field reference data (ground truth). Mereka menggunakan sekitar 3.500 gambar untuk melatih sistem tersebut. Gambar-gambar ini menunjukkan area hutan dan non-hutan di Kalimantan dan Sumatra. Sistem tersebut harus diajari apa yang harus dicari. Metode Random Forest menggunakan 500 cara untuk membuat keputusan. Metode lain, yang disebut CNN, melihat gambar-gambar tersebut dengan cara tertentu. Ia belajar dari kesalahannya dan menjadi lebih baik seiring waktu. Orang-orang yang mengerjakan proyek ini memilih pengaturan ini karena pengaturan tersebut bekerja dengan baik di masa lalu dan ketika mereka mencobanya. Mereka ingin sistem tersebut mampu membedakan antara area hutan dan non-hutan. Kelas hutan dan non-hutan digunakan agar sistem dapat bekerja dengan benar. Model evaluation was conducted using a confusion matrix, overall accuracy, and the Kappa coefficient (Li et al., 2022; Zhang et al., 2020).

d. Change Detection

Forest cover change analysis was performed using post-classification comparison and time-series analysis methods to identify areas experiencing deforestation. Classification results from 2013 were compared with those from 2023 to determine the extent and spatial distribution of deforestation (Sun et al., 2020).

e. Result Validation

Validation was carried out by comparing classification results with field observation data and reference data from the Global Forest Change (GFC) dataset by Hansen et al. (2013). Validation outcomes are presented in the form of error matrices and accuracy statistics for each algorithm used.

5. Data Analysis

The results were analyzed quantitatively by calculating:

- The area of deforestation per province and per year.
- The percentage of forest cover change relative to the total forest area.

- The spatial distribution of deforestation visualized through thematic maps using ArcGIS Pro and QGIS.
- The performance evaluation of AI models based on accuracy, precision, recall, and F1-score.

Additionally, correlation analysis was conducted between detected deforestation and key driving factors such as fire intensity, population density, and plantation expansion.

6. Ethics and Research Limitations

This study adheres to open data principles and does not utilize restricted or classified satellite imagery. The main limitations include the influence of cloud cover in tropical regions and limited availability of direct field data for validation, which were addressed through the use of Sentinel-1 radar imagery.

RESULTS AND DISCUSSION

1. Results of Satellite Image Analysis

Satellite image analysis using Artificial Intelligence (AI)–based algorithms, particularly the Convolutional Neural Network (CNN) model, successfully identified deforestation areas in Kalimantan and Sumatra during the 2015–2024 period. Based on the classification results of Landsat 8 and Sentinel-2 imagery that had undergone preprocessing steps (atmospheric correction, cloud masking, and temporal compositing), the model achieved an accuracy rate of 92.4%, with a Kappa coefficient value of 0.89.

The resulting detection maps indicate that Central Kalimantan and South Sumatra experienced the most significant forest cover decline. In Kalimantan, deforestation was concentrated around oil palm plantation areas and coal mining sites, while in Sumatra, the largest changes occurred on peatlands converted into agricultural land and industrial plantations (Hansen et al., 2023; Gaveau et al., 2022).

2. Spatial Patterns of Deforestation

The spatial analysis results reveal a pattern of deforestation shifting from coastal areas toward inland regions. In Kalimantan, deforestation tends to follow linear patterns along road networks and rivers, indicating a strong linkage between infrastructure development and new land clearing. In Sumatra, deforestation patterns form large clusters in areas close to industrial concessions and newly developed settlements.

The involvement of AI enables faster and more accurate detection of forest cover changes compared to conventional visual interpretation methods. By using Random Forest and deep learning algorithms, the system can process large-scale multi-temporal imagery efficiently with reduced computational time (Zhang et al., 2022).

The AI algorithms that were tested were compared to each other. The CNN model did the job of classifying things. This is because it is good at looking at satellite pictures and finding patterns and differences in texture. The Random Forest model was also pretty good. Did not need as much computer power to work. On the hand the SVM model did not do as well in areas where the land cover was very mixed up.

These results show that using deep learning methods is a way to monitor deforestation on a large scale. This is especially true when we have quality pictures to work with. The CNN model and other deep learning methods like it are very good, at looking at these pictures and finding the information we need. Deep learning approaches are the way to go for large-scale deforestation monitoring.

3. Comparison with Field Data

Validation of the analysis results was conducted by comparing model predictions with field data collected by the Ministry of Environment and Forestry (MoEF) in 2023. The validation results show a consistency rate of 87.6%, indicating that the AI-based approach is reliable for monitoring forest cover changes in Indonesia.
In addition, the use of supplementary data such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) improved accuracy in distinguishing primary forest, secondary forest, and non-forest areas. The combination of multispectral data and machine learning algorithms was also effective in addressing cloud and shadow issues commonly encountered in tropical satellite imagery (Bai et al., 2021).

4. Implications and Discussion

The findings of this study demonstrate that the integration of satellite imagery and artificial intelligence can serve as a powerful tool for an early warning system for deforestation in Indonesia. The use of AI enables government agencies and environmental organizations to monitor changes in near real time and identify priority areas for conservation. Nevertheless, challenges remain, including the limited availability of high-resolution data, constrained computational capacity in regional areas, and the need to integrate socio-economic data to better understand the underlying drivers of deforestation (Margono et al., 2023). Therefore, collaboration among research institutions, universities, and government agencies is essential to strengthen technology-based forest monitoring systems.

The results we got in this study are much the same as what other people found out before. For example Herdiansyah et al. (2022) And Pham et al. (2021) Said that using AI is a way to figure out what is covered by forest. We got it right 92.4 percent of the time which shows that AI models can really help us keep an eye on the forests. The AI models for forest-cover classification are really good. Using pictures from different satellites also helps us find things more easily in places, near the equator where it is often cloudy. The forest-cover classification is better when we use different satellite pictures.

CONCLUSION

This study demonstrates that the utilization of Artificial Intelligence (AI) technology in satellite image analysis can effectively enhance deforestation monitoring capabilities in Indonesia, particularly in the regions of Kalimantan and Sumatra. By applying a combination of Convolutional Neural Network (CNN) and Random Forest algorithms, the system was able to identify areas of forest cover loss with a high level of accuracy, reaching 92.4%.

The analysis results reveal that deforestation patterns in both regions are closely linked to human activities, especially the expansion of oil palm plantations, mining operations, and infrastructure development. Central Kalimantan and South Sumatra were recorded as the regions with the highest rates of forest loss over the past decade.

The integration of medium-resolution satellite imagery (Landsat 8 and Sentinel-2) with AI-based approaches has proven to be efficient in generating rapid and continuous forest cover change maps. This approach also offers significant potential for the implementation of deforestation early warning systems that can support government policies in conservation efforts and climate change mitigation.

Nevertheless, this study also identifies several challenges, including the limited availability of high-resolution data, cloud interference in tropical imagery, and the need to improve computational capacity and human resources at the local level. Therefore, future research is recommended to integrate socio-economic data, climate data, and other spatial information to achieve a more holistic understanding of deforestation drivers and to better support evidence-based decision-making.

The study we did has some ideas for people who take care of the environment and make rules to protect forests in Indonesia. We found out that our computer model is really good at predicting things it is about 92.4% of the time and when we checked it again it was still good about 87.6% of the time. This means that we can use computers to watch the forests and help people make decisions and catch problems early. These results show that if we use computers to watch the forests often the government will be able to find the areas that need help the most and stop bad things from happening to the forests faster. Forest conservation is very important and using computers to help with forest monitoring can make a difference, for environmental management and forest conservation policies in Indonesia.

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