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Mapping Deforestation in The Tamiang Watershed Through NDVI Analysis of Sentinel-2 Imagery Based on Google Earth Engine

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ABSTRACT

The Tamiang Watershed (DAS) faces pressure from human activities that cause deforestation and threaten water resource sustainability. This study aims to map and measure land cover changes, especially deforestation, in the Tamiang Watershed from 2021 to 2025. It uses the Google Earth Engine (GEE) cloud platform to analyse annual median composite images from Sentinel-2. The Normalized Difference Vegetation Index (NDVI) analysis reclassifies land cover into four categories. Change detection employs the post-classification comparison method to identify land conversions. Results reveal significant net deforestation, with high-density vegetation (forest) decreasing by 133.39 km² over five years. This loss was mainly converted into medium and low-density vegation, which rose sharply by 103.50 km². The findings highlight a rapid land clearing rate that threatens watershed degradation. The study recommends strengthening integrated, cross-jurisdictional watershed management and adopting machine learning techniques for future predictive analysis.

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1. INTRODUCTION

Forest areas serve as crucial buffers for global and regional ecosystems. Ecologically, forests regulate the hydrological cycle, act as carbon sinks, and provide vital habitats for biodiversity (Ramadhan, 2025). The ecosystem services they deliver, such as clean water and air, directly support human life (de Mendonça et al., 2025). The stability of this ecosystem relies heavily on the integrity of vegetated land cover. Disturbances to forest areas can disrupt these essential functions, leading to declines in environmental quality and increased vulnerability to disasters (Carl Lewis Kapitarauw et al., 2023). In recent decades, pressure on forest ecosystems has risen significantly due to community activities. The growing demand for land for settlements, large-scale agricultural expansion, infrastructure development, and extractive economic activities has driven extensive land conversion and deforestation (Dariono et al., 2018). This landscape transformation—from natural vegetation to built-up or monoculture land—is a primary driver of environmental degradation. Not only does this process remove biomass, but it also alters the biophysical characteristics of the land surface, directly impacting the hydrological balance of a watershed.

The Tamiang Watershed in Aceh Tamiang Regency, Aceh Province, exemplifies the effects of uncontrolled land conversion (Fani et al., 2024). As an essential hydrological unit in Aceh Province, it faces intense pressure, leading to significant degradation. The loss of vegetation in the upstream area directly affects the dynamics of the hydrological cycle. Data indicate reduced river discharge during the dry season, which endangers the community's raw water supply (Fani et al., 2024; Ramadhini & Sukojo, 2017). Meanwhile, during the rainy season, the land's reduced capacity to absorb rainwater, resulting from vegetation loss, leads to increased surface runoff and intensification of annual floods. This not only increases the frequency and severity of floods but also accelerates soil erosion, resulting in higher water turbidity. The extensive scale of deforestation necessitates monitoring methods that are effective, affordable, and capable of covering large areas (Viedra & Sukojo, 2023). Traditional terrestrial survey techniques, while precise, are often limited by high costs, lengthy durations, and accessibility challenges in remote locations. In response, advancements in remote sensing technology and large-scale geospatial data processing provide an innovative solution. The availability of open-source multispectral satellite imagery, like Sentinel-2, with high temporal resolution, enables regular monitoring of land cover changes at a scale suitable for watershed analysis (Alvarez-Mendoza et al., 2024; Qasimi et al., 2022).

However, the massive volume of data produced by satellite constellations, such as Sentinel-2, creates computational challenges related to storage and processing. Cloud computing platforms such as Google Earth Engine (GEE) have emerged as solutions to these issues. GEE offers access to a petabyte-scale archive of geospatial data along with server-side parallel processing capabilities, allowing researchers to perform complex time-series analyses without the need for high-performance local computing infrastructure (Gorelick et al., 2017). Google Earth Engine (GEE) represents a paradigm shift for large-scale forestry and watershed monitoring. Its cloud-based architecture provides unprecedented access to petabyte-scale geospatial archives, including Sentinel and Landsat data, coupled with high-performance, parallel-processing capabilities. This eliminates the traditional barriers of local data acquisition and computational power. For forestry, GEE enables dense time-series analysis to quantify deforestation, forest degradation, and reforestation dynamics at high temporal and spatial resolutions. For watershed management, it facilitates the integrated analysis of land-use change across entire basins, allowing scientists to directly model the hydrological impacts of upstream deforestation on downstream water resources (Ghimire et al., 2025). The findings of this analysis provide essential spatial data to stakeholders and policymakers. Information on the location, extent, and rate of deforestation can form a scientific foundation for developing targeted conservation strategies, sustainable spatial planning, and hydrometeorological disaster mitigation efforts. Consequently, this technology-driven

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monitoring directly supports efforts to promote ecological sustainability and environmental resilience in the Tamiang Watershed over the long term.

2. METHODS

2.1. Research Location and Time

This research focused on the Tamiang Watershed, a crucial hydrological unit located in Aceh Province, Indonesia. The Tamiang Watershed plays a crucial role in supporting community life by providing essential water resources for agriculture, raw water, and fisheries. The total area of the Tamiang Watershed that became the Area of Interest (AOI) in this study is approximately 5,620 km². The administrative boundary of this watershed was imported into the analysis environment using a shapefile (DAS Tamiang.shp). The analysis of land cover change focused on five years, comparing land cover conditions in 2021 with conditions in 2025.

2.2. Data and Analysis Platform

The primary data used was multispectral satellite imagery from the COPERNICUS/S2_SR_HARMONIZED (Sentinel-2 Level-2A, Surface Reflectance) collection. This imagery was chosen for its 10-meter spatial resolution in the visible and NIR bands. The entire data processing workflow, from acquisition to visualization, was implemented using the Google Earth Engine (GEE) cloud computing platform. Interaction with the GEE API was conducted through the Google Colaboratory (Google Colab) environment using the Python language. The geemap library served as the primary interface to authenticate, call, and analyze GEE data within the Colab notebook.

2.3. Data Analysis Stages

The research workflow consisted of several systematic computational stages executed in GEE.

2.3.1. Pre-processing Cloud-Free Annual Composite

The first stage involved creating clean annual composite images for 2021 and 2025. For each year, images were filtered based on the AOI boundary (Tamiang Watershed) and date range (January 1 to December 31). A cloud masking process was applied using a specific function that utilizes the 'QA60' band to identify and remove cloud (Bit 10) and cirrus (Bit 11) pixels. After obtaining the clean images, the `median()` function was applied to the annual image collection to produce a single representative median composite image for each year.

```
Python
# Function to mask clouds and cirrus from Sentinel-2 SR data
def mask_sentinel2_sr_clouds(image):
qa = image.select('QA60')
# Bit 10 is clouds, Bit 11 is cirrus
cloudBitMask = 1 << 10
cirrusBitMask = 1 << 11
# Mask is 0 (clear) for both bits
mask = qa.bitwiseAnd(cloudBitMask).eq(0).And(
       qa.bitwiseAnd(cirrusBitMask).eq(0))
# Apply mask, scale reflectance (divide by 10000), and clip to AOI
return image.updateMask(mask).divide(10000).clip(das_tamiang)
```

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2.3.2. Vegetation Index Calculation (NDVI)

The second stage was the calculation of the Normalized Difference Vegetation Index (NDVI) for each annual composite image. NDVI was used as the primary proxy to estimate vegetation density and health. This calculation was executed using a function that applied the standard NDVI formula, utilising Band 8 (NIR) and Band 4 (Red) from Sentinel-2.

```
Python
# Function to calculate NDVI from Sentinel-2 SR Harmonized imagery
def calculate_ndvi_sentinel2_sr(image):
# Sentinel-2 SR Harmonized bands: B4 (Red), B8 (NIR)
ndvi = image.normalizedDifference(['B8', 'B4']).rename('NDVI')
return ndvi
```

2.3.3. Land Cover Reclassification

The third stage involved converting the NDVI images (continuous data) into thematic land cover maps (discrete data) through a reclassification process. The NDVI value thresholds for each class were explicitly defined in a Python dictionary data structure, categorised into four classes: water bodies, low-density vegetation, medium-density vegetation, and high-density vegetation. The NDVI images for 2021 and 2025 were then classified using these thresholds, resulting in two thematic land cover maps.

```
Python
# Definition of NDVI thresholds for land cover classification
ndvi_landcover_ranges = {
    'Badan Air': [-1.0, -0.05],
    'Vegetasi Kerapatan Rendah': [-0.05, 0.1],
    'Vegetasi Kerapatan Sedang': [0.1, 0.4],
    'Vegetasi Kerapatan Tinggi’: [0.4, 1.0]
}
```

2.3.4. Change Detection

To map deforestation locations, the post-classification comparison method was applied. The 2025 land cover map (stored as `classified_image_year2`) was compared pixel-by-pixel with the 2021 map (stored as `classified_image_year1`). In GEE, this was executed efficiently using the `.neq()` (not equal) function. Pixels that had different class values between the two years (indicating a change) were given a value of 1, while pixels whose class remained the same were given a value of 0. The result was a binary image (`difference_image`) that spatially shows the locations where land cover changes occurred within the Tamiang Watershed.

```
Python
# Accessing the classified images for 2021 and 2025
classified_image_year1 = yearly_classified_images.get(2021)
classified_image_year2 = yearly_classified_images.get(2025)

# Calculating the difference (change detection)
difference_image = classified_image_year2.neq(classified_image_year1) \
                                          .rename('Change')
```

2.3.5. Area Quantification

The final stage involved quantifying the area for each land cover class in 2021 and 2025, as well as the total area that changed. This calculation utilized the `ee.Image.pixelArea()` function, which accurately calculates the area of each pixel in square meters. This area was

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then summed (aggregated) for each class using `reduceRegion()` with an analysis scale (resolution) of 30 meters. The result from `reduceRegion()` (in square meters) was then converted to square kilometres (km²) and tabulated into a CSV file for land change balance analysis, mainly to track the conversion from the 'High-Density Vegetation' class to other classes as an indicator of deforestation.

```
Python
# Menghitung luas area (dalam meter persegi)
# 'class_mask' adalah citra biner untuk satu kelas spesifik
area_sq_m_image = class_mask.multiply(ee.Image.pixelArea())
# Menjumlahkan total luas untuk geometri DAS Tamiang
total_area_sq_m = area_sq_m_image.reduceRegion(
    reducer=ee.Reducer.sum(),
    geometry=das_tamiang.geometry(),
    scale=60,  # Skala resolusi analisis
    maxPixels=1e9
).getInfo()
```

3. RESULTS AND DISCUSSION

Hydrologically, the Tamiang Watershed crosses three administrative regions: Aceh Tamiang Regency, East Aceh Regency, and Langsa City. This presents a fundamental challenge to the urgency of integrated watershed management. The basic principle of watershed management is to view the ecosystem as a single, upstream-downstream unit, where administrative boundaries should not hinder effective watershed management. Activities in the upstream area, located in the East Aceh Regency, will have a direct biophysical impact on the middle and downstream regions, which are located in Aceh Tamiang Regency and Langsa City. Land degradation or deforestation in the upstream will manifest as increased flood frequency, heavy sedimentation, and decreased water quality downstream. Therefore, a sectoral or partial approach that only focuses on one regency/city is guaranteed to be ineffective. Figure 1 shows the location and coverage of the Tamiang Watershed area.

Based on data analysis from 2021 to 2025 (Figure 2 and Figure 3, significant land cover change dynamics are visible in the Tamiang Watershed, indicating a deforestation process. The primary focus of this change is the consistent reduction of high-density vegetation (forest), which shrank from 5,190.35 km² in 2021 to 5,056.96 km² in 2025. This signifies a net deforestation of 133.39 km² during those five years. This loss of forest cover was directly converted into the other three land cover categories, all of which experienced an increase in area. The largest conversion occurred in low-density vegetation (including open land, degraded land, or settlements), which experienced a significant surge of more than threefold, from 34.07 km² in 2021 to 137.57 km² in 2025, a total addition of 103.50 km². This is the strongest indicator of forest land clearing.

In addition, medium-density vegetation (including shrubs or plantations) also experienced an increase, albeit more moderate, from 345.88 km² to 364.24 km², or an increase of 18.36 km². The Water Body category also showed expansion, increasing by 11.53 km² (from 50.11 km² to 61.64 km²), which may indicate the opening of new ponds or river widening due to erosion. Overall, the data shows a clear change balance: 133.39 km² of forest (high-density vegetation) has been lost and converted primarily into open land (low-density and medium-density vegetation), which is the classic definition of deforestation and land degradation. Specifically, the vegetation density dynamics of the Tamiang Watershed can be seen in Figure 2 and Figure 3.

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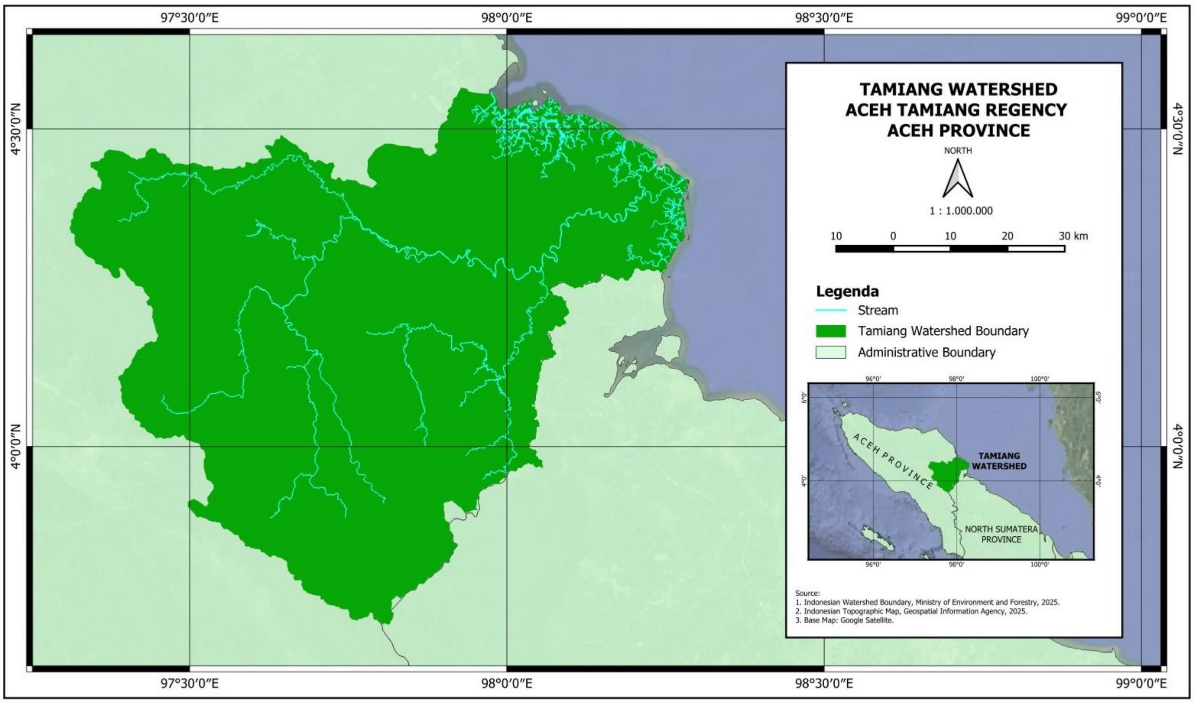

Figure 1. Location of the Tamiang Watershed, Aceh Tamiang Regency, Aceh Province.

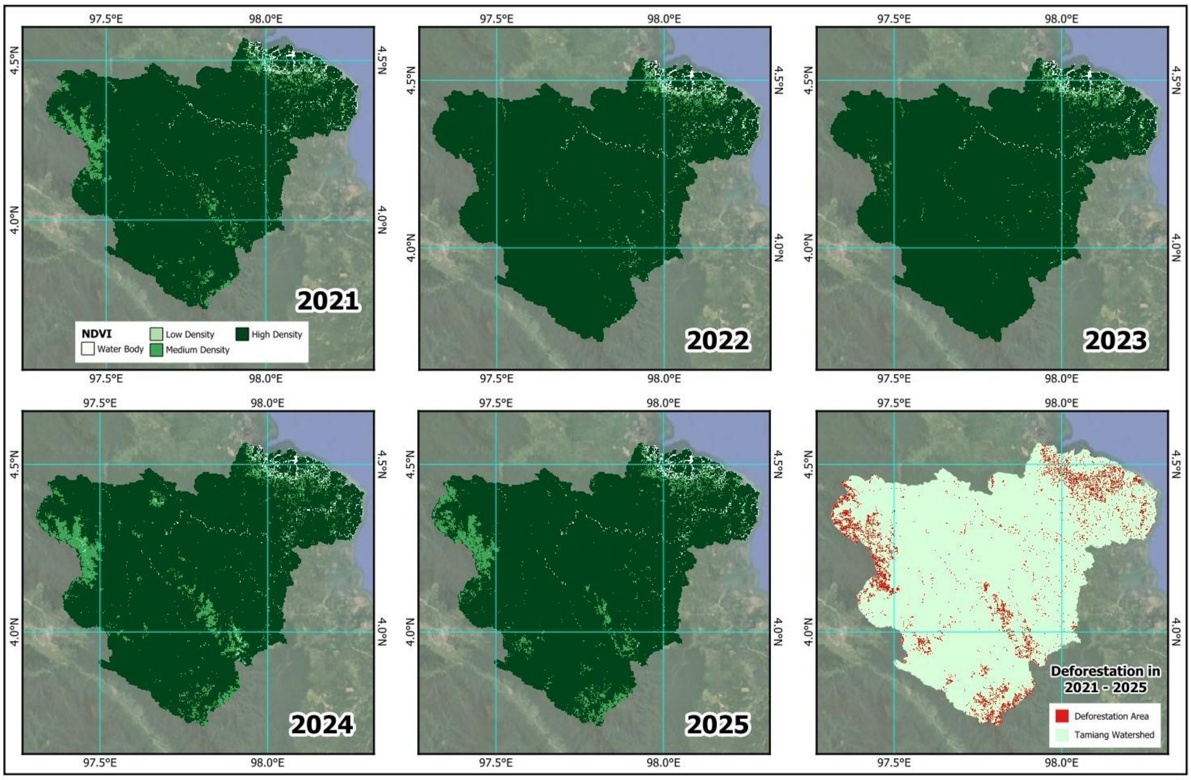

Figure 2. Dynamics of vegetation density in the Tamiang Watershed from 2021 to 2025 and deforestation 2021-2025.)

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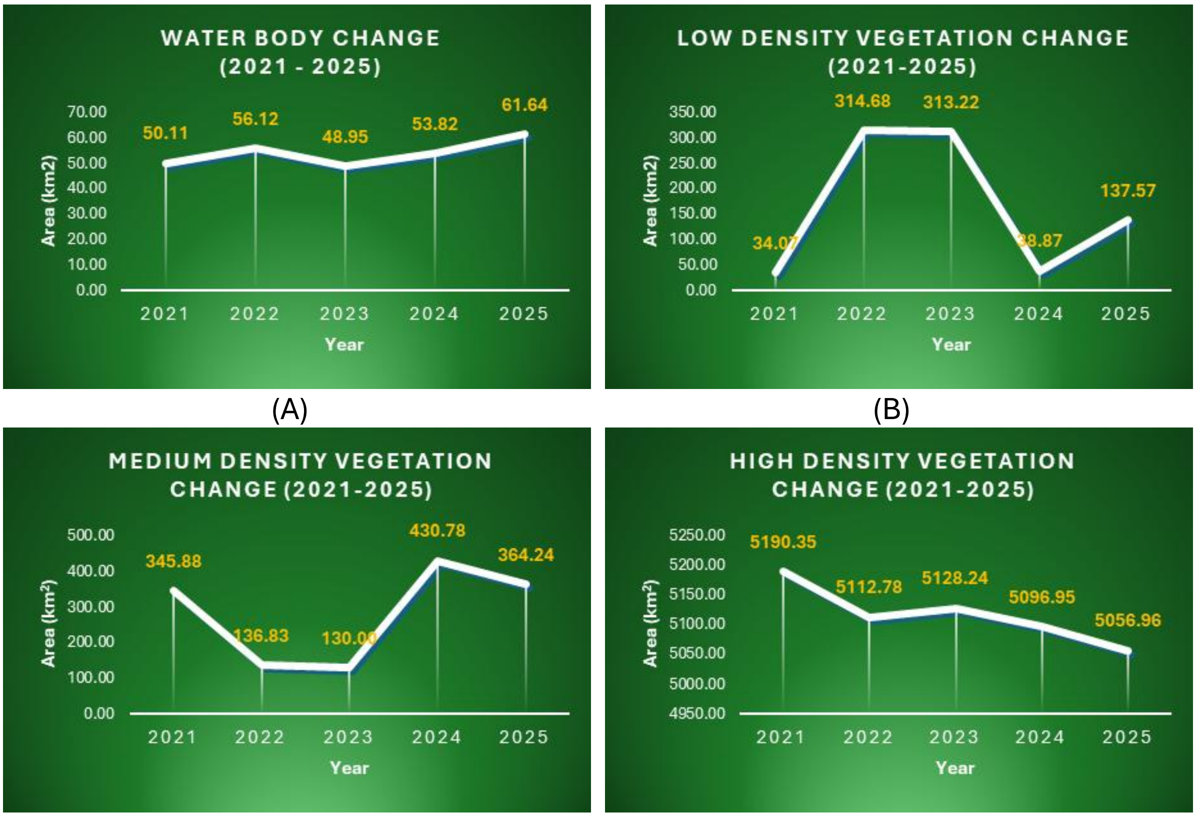

Figure 3. Graph of land area change based on NDVI analysis in the Tamiang Watershed.

The quantitative analysis of land-use change within the Tamiang Watershed shows a significant net loss of 133.39 km² of high-density vegetation between 2021 and 2025. This landscape degradation is not a random natural process but a clear spatial result of intense human activities. The increase in areas classified as medium and low-density vegetation strongly suggests a systemic conversion of primary forest cover. This conversion indicates land clearing driven by nearby causes such as expanding agricultural plantations, new settlements, and various extractive activities (Tambunana et al., 2020). This human footprint is the main driver causing a chain of negative environmental effects, posing a direct and serious threat to the watershed's hydrological integrity and long-term water resource sustainability.

The causal link between this deforestation and regional water security mainly depends on how the forest acts as a vital biological and physical regulator. Unbroken forest ecosystems serve as a 'natural sponge,' managing the watershed's water cycle. The layered forest canopy captures rainfall, reducing the erosive power of rain, while the deep root systems and rich organic matter in the soil encourage high infiltration rates. This process is crucial for allowing water to percolate into the ground, which helps recharge underground aquifers. These aquifers are essential sources that keep river baseflow steady, providing a reliable water supply, especially during long dry spells.

Deforestation systematically dismantles this vital function. The removal of vegetation cover and subsequent soil compaction—often caused by heavy machinery or conversion to monoculture agriculture—dramatically reduces the soil's infiltration capacity. As a result, precipitation that was once absorbed gets turned into rapid surface runoff (Ramadhan, 2025).

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This disruption causes a severe imbalance in the hydrological system, creating a dual crisis of water scarcity and water-related hazards. First, during the rainy season, the faster surface runoff results in a more unpredictable and intense hydrological response. River systems, unable to absorb the sudden water influx, become overwhelmed, leading to an increase in the frequency and size of peak discharge events, or floods, downstream. This high-speed runoff speeds up soil erosion in the washed-out uplands, carrying large amounts of sediment into rivers. This raises turbidity levels (Ramadhini & Sukojo, 2017), which harms water quality for humans and aquatic life, while also causing river channel siltation, decreasing channel capacity, and further increasing flood risks.

Secondly, the impact remains just as severe during the dry season. Reduced infiltration decreases groundwater recharge. As a result, river systems, which depend on steady groundwater discharge to maintain their baseflow, experience significantly lower discharge levels. This leads to critical water shortages and intensifies drought conditions, threatening the viability of agriculture and the availability of drinking water for communities relying on the Tamiang River. In essence, the 133.39 km^2 of observed deforestation is not just a loss of forest cover but a major failure of vital ecosystem infrastructure, directly affecting the sustainability of water resources throughout the entire region.

The key role of geospatial technologies such as Remote Sensing (RS) with imagery like Sentinel-2 is an effective method for monitoring this degradation accurately and periodically over a broad watershed scale. Additionally, Geographic Information Systems (GIS) provide spatial context by linking deforestation sites with infrastructure (roads) or administrative boundaries, thereby revealing human activity patterns. In the future, big geospatial data analysis will shift from simple monitoring (descriptive) to forecasting (predictive). The use of Machine Learning (ML), Deep Learning (DL), and GeoAI not only allows for mapping deforestation that has already occurred but also analysing complex non-linear patterns—such as proximity to new roads, global commodity prices, and settlement patterns—to predict where deforestation hotspots will emerge in the future (Abdo et al., 2025).

This technology represents a move from reactive management to proactive intervention for watershed sustainability, which should be studied by the scientific community to ensure the Earth's ecosystem remains sustainable. This challenge is becoming increasingly urgent, as global climate change and ecosystem degradation are expected to intensify and become more unpredictable. Climate change not only raises temperatures but also changes precipitation patterns, increasing the frequency and severity of extreme weather events like prolonged droughts and flash floods. In a watershed context, the effects of local deforestation will be exponentially worsened by these climate shocks. An ecosystem that has been degraded loses its resilience, making reactive management insufficient. We can no longer merely map the damage that has been done; we must also be able to anticipate how this fragile ecosystem will respond to various future climate scenarios.

The capabilities of GeoAI, ML, and DL become essential for modelling these complex scenarios. This technology can simulate feedback loops—for example, how upstream deforestation, when combined with extreme rainfall patterns caused by climate change, will influence peak flood discharge downstream. Therefore, the use of proactive AI technology is no longer merely innovative but a vital necessity for disaster adaptation and mitigation strategies, ensuring that interventions today can address the significantly greater ecosystem challenges of the future.

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4. CONCLUSION

The implementation of the Google Earth Engine (GEE) platform using Sentinel-2 imagery and NDVI analysis proved to be an effective and efficient method for monitoring deforestation at the watershed scale. This study concludes that significant net deforestation took place in the Tamiang Watershed during 2021-2025. It was recorded that the area of high-density vegetation (forest) cover shrank by 133.39 km². The loss of this forest cover was mainly converted into low-density vegetation (open or degraded land), which increased sharply by 103.50 km². This phenomenon strongly indicates that human activity is the main driver of land conversion. Cloud-based geospatial technology provides vital quantitative evidence of watershed degradation, directly affecting hydrological functions and water resource sustainability in the region. Given the substantial deforestation findings, urgent policy responses are necessary. It is recommended that stakeholders, particularly governments in the three jurisdictions (Aceh Tamiang Regency, East Aceh Regency, and Langsa City), enhance coordination in integrated watershed management. The spatial data from this research can serve as a scientific basis for strengthening Regional Spatial Plans (RTRW), supervising permits, and prioritising land rehabilitation programmes in degraded areas, especially in upstream sub-watersheds. For future research, it is advised to incorporate machine learning methods (such as Random Forest) or deep learning algorithms within GEE. These approaches can improve classification accuracy and enable more detailed distinction of land conversion types (e.g., into settlements, palm oil plantations, or mining land), thereby sharpening analysis of deforestation drivers.

5. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

7. REFERENCES

Abdo, H. G., Richi, S. M., Zeng, T., Alqadhi, S., Prasad, P., Nguyen-Huy, T., Alharbi, M. M., & Mallick, J. (2025). Machine learning-based assessment of flood susceptibility in the Eastern Mediterranean: a case study of Baniyas River basin. Geomatics, Natural Hazards and Risk, 16(1). https://doi.org/10.1080/19475705.2025.2524417

Alvarez-Mendoza, C.-I., Mollocana, J.-G., & Gualotuna, D. (2024). Mapping of NDVI in Ecuador During the Last 20 Years Using the Google Earth Engine Cloud Geospatial Tool (pp. 3–13). https://doi.org/10.1007/978-3-031-70981-4_1

Carl Lewis Kapitarauw, Christian S. Imburi, & Matheus Beljai. (2023). Analisis Spasial Deforestasi Kawasan Hutan Lindung Arfak di Kabupaten Manokwari. JURNAL KEHUTANAN PAPUASIA, 9(1), 109–122. https://doi.org/10.46703/jurnalpapuasia.Vol9.Iss1.434

Dariono, D., Siregar, Y. I., & Nofrizal, N. (2018). Analisis Spasial Deforestasi dan Degradasi Hutan di Suaka Margasatwa Kerumutan Provinsi Riau. Dinamika Lingkungan Indonesia, 5(1), 27. https://doi.org/10.31258/dli.5.1.p.27-33 de Mendonça, G. C., Abdo, M. T. V. N., da Costa, L. M., Costa, R. C. A., Pacheco, F. A. L., Ribeiro, M. C., Zakia, M. J. B., Borma, L. D. S., & Pissarra, T. C. T. (2025). Watershed's spatial targeting: Enhancing payments for ecosystem services to scale up agroecosystem restoration through nature-based solutions. Ecosystem Services, 71, 101679. https://doi.org/10.1016/j.ecoser.2024.101679

Fani, D. R., Muslih, A. M., & Anhar, A. (2024). Analisis Spasial Laju Deforestasi di Kawasan Hutan Kabupaten Aceh Tamiang, Provinsi Aceh. Jurnal Ilmiah Mahasiswa Pertanian, 9(2), 430–440. https://doi.org/10.17969/jimfp.v9i2.29879

Ghimire, P., Karki, S., Pandey, V. P., & Pradhan, A. M. S. (2025). Mapping Spatio-Temporal dynamics of irrigated agriculture in Nepal using MODIS NDVI and statistical data with Google Earth Engine: A step towards improved irrigation planning. International Journal of Applied Earth Observation and Geoinformation, 136, 104345. https://doi.org/10.1016/j.jag.2024.104345

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Qasimi, A. B., Isazade, V., Kaplan, G., & Nadry, Z. (2022). Spatiotemporal and multi-sensor analysis of surface temperature, NDVI, and precipitation using google earth engine cloud computing platform. Russian Journal of Earth Sciences, 1–12. https://doi.org/10.2205/2022ES000812

Ramadhan, L. P. (2025). Analisis Deforestasi dan Degradasi Terhadap Lingkungan Hidup. Beleid, 3(1), 91. https://doi.org/10.51825/beleid.v3i1.29470

Ramadhini, M., & Sukojo, B. M. (2017). Analisa NDVI Citra Satelit Landsat Multi Temporal Untuk Pemantauan Deforestasi Hutan Kabupaten Aceh Utara. Jurnal Inotera, 2(1), 23. https://doi.org/10.31572/inotera.Vol2.Iss1.2017.ID16

Tambunana, A., Purba, T., & Rozalina. (2020). Analisis Laju Deforestasi di DAS Bah Bolon berbasis Sistem Informasi Geografis. Jurnal Akar, 9(2), 79–89. https://doi.org/10.36985/jar.v9i2.314

Viedra, G. G. Z., & Sukojo, B. M. (2023). Analysis of The Effect of Deforestation Rates on Air Pollution Concentration and Land Surface Temperature Using Landsat-8 Imagery with Google Earth Engine (Case Study: East Kalimantan Province, 2019-2020). IOP Conference Series: Earth and Environmental Science, 1127(1), 012032. https://doi.org/10.1088/1755-1315/1127/1/012032

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