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Three Decades of Tropical Deforestation on Small Islands Due To Nickel Ore Mining Expansion: The Critical Insight from Indonesia Eastern and Post-Mining Revegetation Recommendations

Khairani Putri Marfi[1,2,3]*, Rahmat Asy'Ari[3,4,5], Abd. Malik A. Madinu[3,4,5], Hanum Resti Saputri[1,2,3], Danik Septianingrum[3,6], Usnil Khotimah[6], Aulia Ulfa[3,6], Alya Raisa Karina[7], Faiza Utami[6,8], Nihawa Hajar Pudjawati[7], Fajar Raihan[9], Muhammad Fikruddin Aslam[7], Ardya Hwardaya Gustawan[7], Moh Zulfajrin[10,11], Lina Lathifah Nurazizah[10,11], Ongky Ongky[10], Hidayat Arismunandar Katili[10,12], Mihwan Sataral[10,12], Fahri Fahri[10,13], Rahmat Pramulya[14], Cecep Kusmana[15]

[1]*SSRS Tropical Deforestation and Degradation Program, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[2]*SSRS EnviroInformatics Labs, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[3]*SSRS Indonesia Tropical Ecological Observatory (InaEco), SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[4]*SSRS EarthInformatics Labs, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[5]*SSRS Indonesia Tropical Earth Observatory (Inarth Indonesia), SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[6]*SSRS Indonesia Biodiversity Hub, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[7]*Pemulihan Bumi Indonesia (Pulih Indonesia), Sustain Group Indonesia, Bogor Regency, Indonesia*
[8]*SSRS Indonesia Tropical Forest Biopharmaca Observatory, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[9]*SSRS Indonesia Revegetation Initiative, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[10]*SSRS Banggai Advanced Research Facility, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[11]*Indonesia Computational Soil Science Group, Bogor Regency, Indonesia*
[12]*Faculty of Agriculture, Tompotika Luwuk University, Luwuk, Banggai Regency, Indonesia*
[13]*Department of Biology, Tadulako University, Palu City, Indonesia*
[14]*SSRS Tropical Agroforestry Program, SSRS Tropical Institute Indonesia, Bogor Regency, Indonesia*
[15]*Department of Silviculture, Faculty of Forestry and Environment, IPB University, Bogor Regency, Indonesia*

* Correspondence: researchkhai@gmail.com

Abstract: Forest cover in Indonesia undergoes annual changes, particularly deforestation resulting from land-use changes. Nickel mining in eastern Indonesia is one of the causes of deforestation, extending even to small islands. Unfortunately, to date, information on deforestation on small islands due to nickel mining remains very limited. Therefore, this study aims to investigate deforestation on seven small islands in eastern Indonesia (across four regencies) caused by nickel ore extraction over the past three decades. Cloud computing via the Google Earth Engine geospatial platform and the machine learning random forest algorithm were employed in this study and proved capable of detecting deforestation across all islands. The most severe deforestation occurred on Gag Island, covering approximately 801 hectares between 1990 and 2025. Pisang Island has the lowest forest cover percentage in 2025, with only 5 hectares, or 19.76%. Forest cover detection using the random forest algorithm yielded the highest accuracy, reaching 0.93 (OA) and 0.86 (KS). This deforestation data represents the first such information for small islands and plays a crucial role in evaluating the negative impacts of nickel mining activities in Indonesia. To mitigate environmental impacts, revegetation efforts are essential for restoring the ecosystem functions of the seven small islands in the study area. The use of cloud computing in remote sensing approaches is considered vital for monitoring forest cover on small islands and can ensure the success of post-mining revegetation.

Keyword: Indonesia deforestation, nickel one mining, remote sensing, small island forest

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INTRODUCTION

Nickel mining expansion in Indonesia has undergone a rapid escalation to the present day, primarily driven by regional and national economic catalysts (Rosada *et al.* 2023; Nasution *et al.* 2024; ChuanYu *et al.* 2024; Sunuhadi *et al.* 2024; Pambudi 2025). This mineral extraction has surged in line with global demand for electric vehicle battery development and other industrial applications (Pandyaswargo *et al.* 2021; Yu *et al.* 2024; Haryadi *et al.* 2024). Consequently, the government continues to facilitate spatial allocations for mining activities within regions identified as strategic nickel resource areas. In Indonesia, nickel reserves are extensively distributed across Sulawesi and Maluku, with localized deposits in Western Papua (Hati *et al.* 2024; Sofianti *et al.* 2025; Pambudi 2025; Atika *et al.* 2026). Nickel extraction

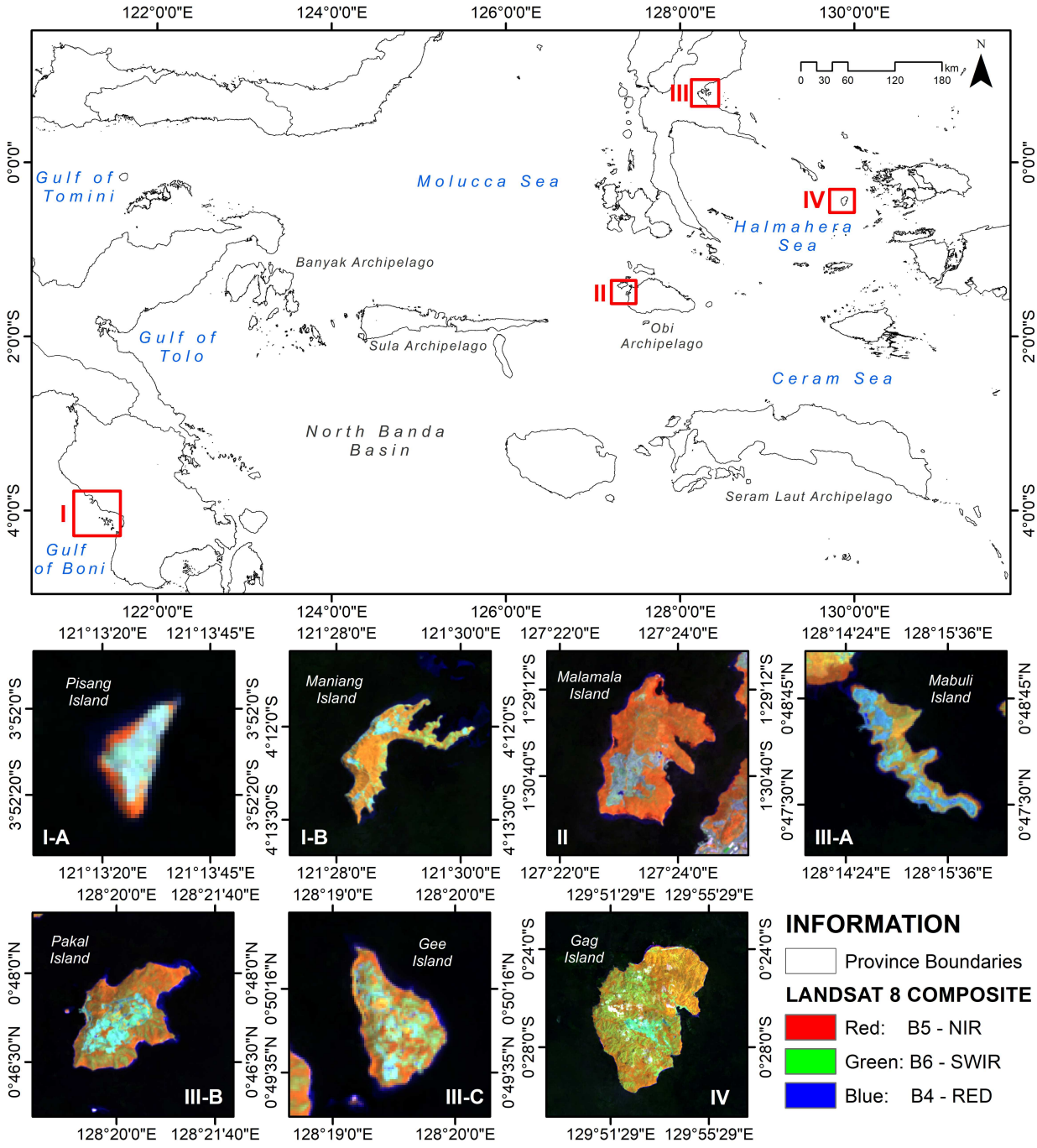


Figure 1. Small island location map in eastern Indonesia

typically employs open-pit mining methods that involve removing multiple layers of topsoil. As a result, the overlying vegetation cover is cleared to access the underlying nickel ore. This process is identified as a primary driver of forest cover depletion attributable to mining activities within the Indonesian territory.

Generally, forest cover loss is extracted using geospatial methods to avoid comprehensive field surveys, which require substantial human and financial resource capacities (Rai *et al.* 2024; Saha *et al.* 2025). Contemporary geospatial technology has advanced significantly, enabling its application across various domains, particularly for vegetation cover monitoring (Pandey *et al.* 2022). Notably, the cloud-based geospatial computing platform launched by Google has emerged as one of the most effective tools for efficiently monitoring Earth surface dynamics (Gorelick *et al.* 2017; Amani *et al.* 2020). This technology mitigates the time-intensive nature of satellite data acquisition, which is often hindered by persistent cloud cover within specific temporal windows. Through cloud computing support, satellite imagery can be seamlessly retrieved and processed using JavaScript-based environments. Consequently, this technology is considered highly suitable for the efficient extraction of forest cover conditions across temporal scales. Previous implementations of the GEE platform include deforestation monitoring in Malaysia by Hu *et al.* (2022), forest degradation in the Brazilian Amazon by Brovelli *et al.* (2020), and deforestation assessments in Indonesia by Perbet *et al.* (2019).

Prolonged deforestation in Eastern Indonesia has emerged as a critical issue of national and global concern, driven by the environmental impacts on local communities. Recurrent ecological disasters have resulted in significant degradation of infrastructure and the socio-economic stability of marginalized populations. This necessitates a detailed evaluation of forest loss attributable to nickel mining and associated activities to foster sustainable forest management frameworks that protect local communities by minimizing environmental impacts. However, enhancing the governance and protection of forest ecosystems on small islands requires fundamental baseline data to support informed decision-making. Unfortunately, empirical information regarding forest degradation specifically linked to nickel extraction remains critically scarce in Indonesia, particularly in its eastern regions. Therefore, this study aims to elucidate tropical deforestation in Eastern Indonesia induced by nickel mining operations, providing essential data to formulate policy recommendations for forest conservation on small islands.

METHODOLOGY

Study Area

Geographically, this study was conducted across several small islands in Eastern Indonesia (Fig. 1). Specifically, the investigation focused on seven small islands currently threatened by nickel mining expansion, which endangers tropical forest cover. These seven islands constitute the Area of Interest (AoI) for this research, spanning four regencies and three provinces (Table 1). The islands vary significantly in spatial extent, ranging from Maniang Island, the smallest at 26.19 ha, to Pakal Island, the largest, encompassing 6036.87 ha.

Table 1. Overview of the location research of a small island based on national data from Indonesia Geospatial Agency (BIG)

Small Islands	Areas (ha)	Regencies	Provinces
Maniang Island	26.10	Kolaka	South East Sulawesi
Pisang Island	399.6	Kolaka	South East Sulawesi
Malamala Island	943.75	South Halmahera	North Maluku
Gag Island	248.61	Raja Ampat	Southwest Papua
Mabuli Island	706.76	East Halmahera	North Maluku
Gee Island	171.97	East Halmahera	North Maluku
Pakal Island	6036.87	East Halmahera	North Maluku

Table 2. Landsat satellite characteristics

Band	Landsat-5	Landsat-8 & Landsat-9
Blue	B1 (0.45-0.52 µm)	B2 (0.452-0.512 µm)
Green	B2 (0.52-0.60 µm)	B3 (0.533-0.590 µm)
Red	B3 (0.63-0.69 µm)	B4 (0.636-0.673 µm)
NIR	B4 (0.77-0.90 µm)	B5 (0.851-0.879 µm)
SWIR1	B5 (1.55-1.75 µm)	B6 (1.566-1.651 µm)
SWIR2	B6 (2.08-2.35 µm)	B7 (2.107-2.294 µm)

Data Sources

The data used consists of open-source multispectral satellite imagery, specifically Landsat imagery. Three Landsat satellites were used in this study: Landsat-5 Thematic Mapper (TM) for mapping in 1990 and a combination of two satellites (Landsat-8 Onboard Operational Land Imager (OLI)-Thermal Infrared Sensor (TIRS) and Landsat-9 OLI2-TIRS2) for mapping mangroves in 2025. The combination of Landsat-8 and Landsat-9 was used to obtain high-quality imagery. All three satellites possess a spatial resolution of 30 meters and temporal resolution (Pengra *et al.* 2015; Olthof *et al.* 2014; Skiles *et al.* 2023). The characteristics of these three Landsat types are detailed in Table 2.

Forest Cover Geospatial Analysis

Forest cover analysis was conducted using supervised learning mapping with satellite remote sensing data for two classification years, namely 1990 and 2025. Landsat imagery was used as a spatial layer to describe land cover conditions at the study site. Forest cover mapping was carried out using the random forest (RF) algorithm on the cloud-computing platform Google Earth Engine (GEE) (Gorelick *et al.* 2017). This took into account GEE's full access to USGS Landsat satellite data resources. Hyperparameter tuning was performed for the random forest (RF) algorithm in GEE, setting ntree to 500. The RF algorithm mapped forest cover into two classes, namely forest and non-forest, using training data amounting to 452 points (classification 2025). In mapping forest cover, RF utilized the characteristics of vegetation, water, and building indices derived from Landsat spectral bands. The list of vegetation, water, and building indices is presented in Table 3.

Accuracy Analysis

Accuracy analysis in this study was conducted using validation data consisting of 28 points for 1990 and 35 points for 2025. The validation points were obtained by determining validation points in each land cover class, in this case, forest and non-forest. The determination of these points was based on visual features in the Landsat RGB layer and was performed directly on the GEE platform. The validation points were selected for the two classification years in accordance with the time setting during the training of the random forest model. Accuracy analysis was performed using a confusion matrix and the following four equations (Eq. 1-4).

$$UA = \frac{X_{ii}}{X_{i+}} \quad \text{.....(Eq. 1)}$$

$$PA = \frac{X_{ii}}{X_{+i}} \quad \text{.....(Eq. 2)}$$

$$OA = \frac{1}{N}\sum_{i=1}^{r} X_{ii} \times 100\% \quad \text{.....(Eq. 3)}$$

$$KS = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{ii}(X_{i+} \times X_{+i})}{N^2 \sum_{i=1}^{r} X_{ii}(X_{i+} \times X_{+i})} \quad \text{.....(Eq. 4)}$$

Information :

UA = User's Accuracy
PA = Producer's Accuracy
OA = Overall Accuracy
KS = Kappa Statistic
X_{ii} = Number of corrected classified samples of class i
X_{i+} = Total number of samples classified as class i (row total)
X_{+i} = Total number of reference samples of class i (column total)

RESULTS AND DISCUSSION

Three Decades of Forest Change in Small Islands

The GEE geospatial platform successfully demonstrated deforestation in the small islands of eastern Indonesia over a three-decade period from 1990 to 2025. According to the 2025 RF algorithm mapping results, all small islands within the monitoring area experienced a decrease in forest cover compared to 1990. Notably, Pisang Island in Kolaka Regency experienced the highest percentage decrease in forest cover, dropping to 5 ha, or approximately 19.76% of its land area by 2025 (Fig. 2). In terms of total area, Gag Island saw the largest decrease in forest area, amounting to approximately 801 ha. This is followed by Malamala

Table 3. Index from the satellite band

Index	Formula	Sources
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{(NIR-Red)}{(NIR+Red)}$	Rouse *et al.* (1974)
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(NIR-Red)}{(NIR+Red+0.5)} \times (1.0 + 0.5)$	Huete (1988)
Enhanced Vegetation Index (EVI)	$EVI = \frac{(NIR-Red)}{(NIR+6\times Red-7.5\times Blue+1)} \times 2.5$	Huete *et al.* (2002)
Atmospherically Resistant Vegetation Index (ARVI)	$ARVI = \frac{(NIR-(Red-(1\times(Blue-Red))))}{(NIR+(Red-(1\times(Blue-Red))))}$	Kaufman *et al.* (1992)
Specific Leaf Area Vegetation Index (SLAVI)	$SLAVI = \frac{NIR}{(Red+SWIR2)}$	Lymburner *et al.* (2000)
Green Normalized Difference Vegetation Index (GNDVI)	$GNDVI = \frac{(NIR-Green)}{(NIR+Green)}$	Gitelson *et al.* (1996)
Ratio Vegetation Index (RVI)	$RVI = \frac{NIR}{Red}$	Pearson and Miller (1972)
Normalized Difference Water Index (NDWI)	$NDWI = \frac{(Green-NIR)}{(Green+NIR)}$	McFeeters (1996)
Augmented Normalized Difference Water Index (ANDWI)	$ANDWI = \frac{(Blue+Green+Red-NIR-SWIR1-SWIR2)}{(Blue+Green+Red+NIR+SWIR1+SWIR2)}$	Rad *et al.* (2021)
Land Surface Water Index (LSWI)	$LSWI = \frac{(NIR-SWIR1)}{(NIR+SWIR1)}$	Xiao *et al.* (2002).
Index-Based Built-up Index (IBI)	$IBI = \frac{\frac{2SWIR1}{SWIR1+NIR}-(\frac{NIR}{NIR+Red}+\frac{Green}{Green+SWIR1})}{\frac{2SWIR1}{SWIR1+NIR}+(\frac{NIR}{NIR+Red}+\frac{Green}{Green+SWIR1})}$	Xu (2008)
Normalized Difference Built-up Index (NDBI)	$NDBI = \frac{(SWIR1-NIR)}{(SWIR1+NIR)}$	Zha *et al.* (2003)

Island (a decrease of 306.17 ha), Pakal Island (279.90 ha), Maniang Island (163.44 ha), Mabuli Island (151.80 ha), Gee Island (92.52 ha), and Pisang Island (20.47 ha). Spatially (Fig. 3), deforestation occurred in the central areas or on the hills' ridges, where nickel mining takes place. Meanwhile, the remaining forest is located along the coastlines. The most severe impacts on coastal forests were observed on Pisang Island, specifically along the eastern coast, and on Mabuli Island, along the western coast. Deforestation in this study represents the first report on forest damage in Indonesia caused by nickel mining on small islands. Findings on land-use changes in mining areas were also documented in the study by Atika *et al.* (2026), which showed changes in vegetation cover from 2013 to 2020. Land cover changes occurring in eastern Indonesia have impacted 7,721 villages on Sulawesi Island (Lo *et al.* 2024). Beyond environmental impacts, nickel mining activities and the presence of nickel mining companies have resulted in socioeconomic impacts on rural communities (Hyldmo *et al.* 2025).

Evaluation of Mapping Accuracy

The use of Landsat data and machine learning in this study proved effective in mapping forest areas on small islands in Indonesia. This is evident from the classification accuracy of Landsat data from 2025, which yielded an Overall Accuracy (OA) of 0.93 and a Kappa (KS) of 0.86. Similar accuracy values were also reported in the study by Katili *et al.* (2025), which achieved an OA of 0.93 and a KS of 0.86 for mangrove mapping in Banggai, Sulawesi Island. Meanwhile, another study by Nurhawaillah *et al.* (2024) on urban forests achieved OA and KS values of 0.90 and 0.82, respectively. As seen in the confusion matrix, the error rate involved 3 non-forest validation points (out of 36

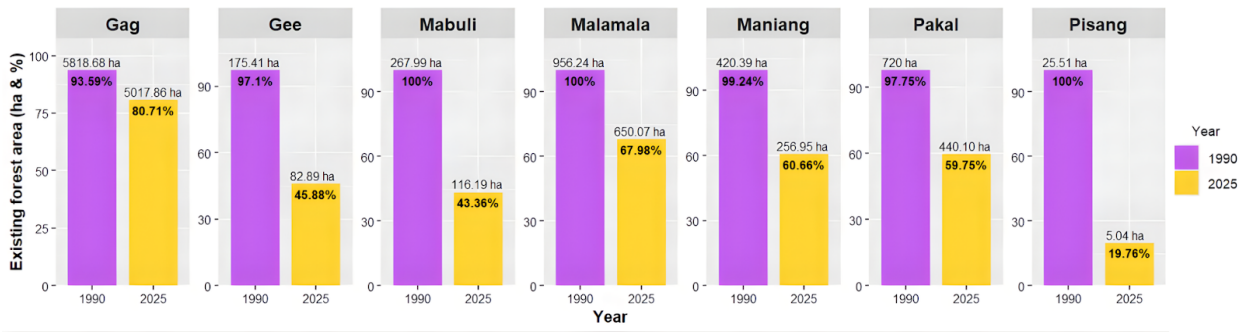


Figure 2. Forest cover 2025 in small islands

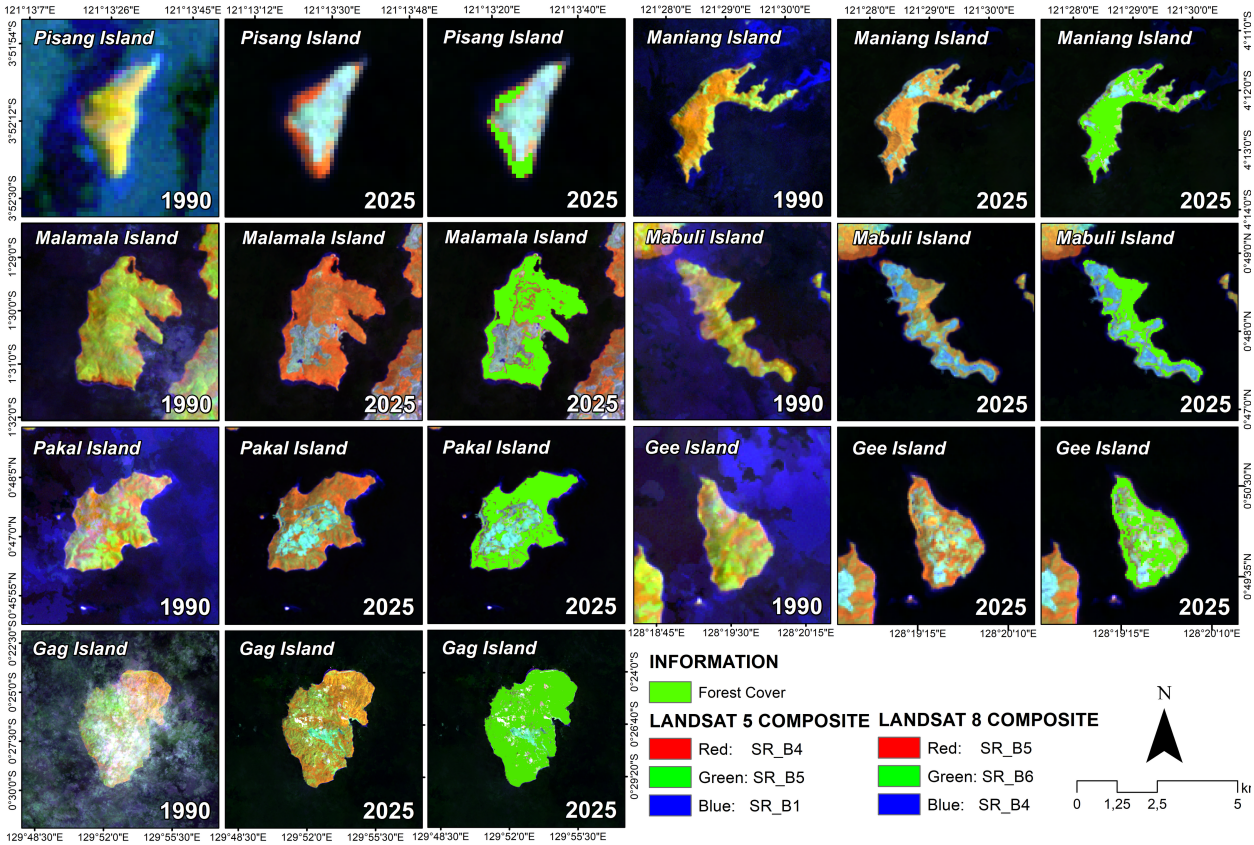


Figure 3. Comparison of the spatial forest condition in 1990 and 2025

total validation points) that were misclassified as forest (Fig. 4). Meanwhile, 2 forest points (out of 34 validation points) were misclassified as non-forest in the mapping results. This resulted in the forest class's Precision (PA) reaching its lowest value of 0.91, compared to the non-forest class's PA of 0.94. Meanwhile, regarding the user error rate (UA), the lowest UA was observed in the non-forest class, at 0.92, compared to 0.94 in the forest class. Compared to previous research, namely Santoso *et al.* (2026), in a case of mangrove mapping using the RF machine learning algorithm, the UA and PA values were low at 0.80 and 0.73, respectively.

Recommendation for Small Island Forest Conservation and Monitoring

Forest conservation on small islands in the study area that are experiencing deforestation is essential. This is because small islands in Indonesia serve essential functions for their surrounding ecosystems, such as providing foraging habitats for migratory bird biodiversity and supporting coral reef ecosystems as a source of fish resources (Germi *et al.*

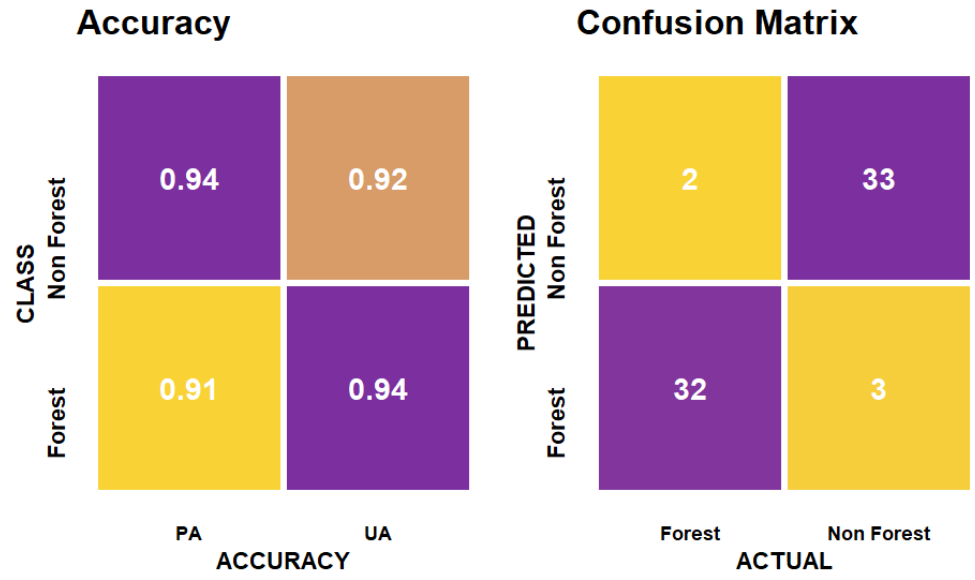


Figure 4. Confusion matrix and accuracy evaluation

2009; Purwanto *et al.* 2015; Reeve *et al.* 2015; Sahetapy *et al.* 2018; Ahmad *et al.* 2020; Teniwut *et al.* 2023; Mujiyanto *et al.* 2026). If forest areas on small islands are damaged or fail to recover, this is projected to disrupt the food chain for migratory bird biodiversity. Meanwhile, the surrounding coral reef ecosystems will suffer damage if erosion continues due to the loss of vegetation cover's function in controlling rain-induced erosion. Therefore, these two examples of the role of forest cover on small islands lead to recommendations for immediate restoration efforts for the 7 small islands in this study that nickel mining activities have damaged. Environmental restoration can be achieved through post-mining revegetation on the mine site. Post-mining revegetation efforts can utilize important, rare, and endemic species in the study area to restore the forest ecosystem's functions for the small islands. For example, in the areas of Malamala Island and Gag Island, endangered endemic species that produce strong timber can be used, such as the dipterocarp forest species Rubroshorea selanica (Kamila *et al.* 2025). This is because local species can be easily obtained from their native regions, thereby enhancing the operational efficiency of the revegetation phase (Pratiwi *et al.* 2021). Fruit-bearing tree species are also an option for accelerating environmental recovery by producing fruits that can be eaten by wildlife. The presence of wildlife in forest restoration areas is considered to play a dual role in seed dispersal, thereby accelerating natural regeneration (Holbrook and Smith 2000; Anggraini *et al.* 2001; Bravo 2021). Additionally, agroforestry systems can be applied in post-mining revegetation areas to enhance local communities' access to economic resources. This is because agroforestry systems can provide food for local communities and high-value economic commodities (Hermawan 2016; Rusdiana *et al.* 2026). Beyond economic impacts, agroforestry can contribute to soil organic carbon (SOC) through litter production (Pramulya *et al.* 2026).

Efforts to protect forests and rehabilitate post-mining areas can be carried out using remote sensing technology. This study provides technical recommendations for future research, stakeholders (both national and regional), and nickel mining companies in eastern Indonesia to use and leverage cloud-based remote sensing technology for monitoring forest cover and rehabilitation areas. As done by Alamako *et al.* (2024), who used cloud-computing-based remote sensing technology to monitor post-coal mining revegetation areas between 2016 and 2023, covering 1,234 ha. The use of cloud-computing-based remote sensing technology is intended to prevent uncontrolled failures in rehabilitation areas, enabling early anticipation and the implementation of reforestation. The efficiency of cloud computing-based revegetation area monitoring practices is recommended to achieve sustainable mining management. Additionally, this effort can also support national ambitions to reduce carbon emissions from the land use sector to achieve the FOLU Net Sink 2030 (Forestry and Other Land

Use - Net Sink 2030) as part of Indonesia's commitment under the Enhanced National Determined Contribution (Enhanced NDC) each year, as stipulated in the Minister of Environment and Forestry Decree No. 168/Menlhk/PKTL/PLA.1/2/2022.

CONCLUSIONS

Nickel mining has expanded in eastern Indonesia, eroding forest cover and potentially causing environmental impacts. Deforestation in this region was analyzed at the small-island level using a random forest algorithm applied to Landsat data from 1990 and 2025. The analysis yielded deforestation data for seven small islands across four regencies. Gag Island experienced the most severe deforestation, reaching approximately 801 hectares. Meanwhile, Pisang Island is the small island with the largest percentage decrease in forest cover, leaving only about 19.76% or approximately 5 hectares. This deforestation data was acquired via cloud computing using the GEE geospatial platform, achieving accuracy levels of 0.93 (OA) and 0.86 (KS). Environmental restoration through revegetation is recommended to mitigate the environmental impacts resulting from land-use changes due to nickel mining. Revegetation efforts can involve rare species and complex agroforestry systems to enhance the ecosystem role of post-mining revegetation areas. The use of GEE is highly recommended for future research as well as for stakeholders to improve the efficiency of monitoring revegetation areas, thereby reducing growth phase failures in nutrient-poor post-mining lands.

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