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Extractive Economics and the Environment: An Evaluation of the Role of Mineral Mines on Regional Deforestation

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Abstract

Background: Mineral mining plays a major role in Indonesia's economy, but it also places considerable pressure on forest ecosystems, creating a paradox between extractive economic growth and environmental sustainability. **Objective:** This study aims to analyze the impact of the mineral mining sector on deforestation in Indonesia. **Methods:** A quantitative approach was applied using panel data from 34 provinces over the period 2020–2024. Independent variables included the mining sector's GDP, population, the Human Development Index (HDI), and dummy variables for the presence of metal and non-metal mines. Data were analyzed using a Random Effects Model, decision tree analysis, and geo-map visualization. **Results:** Mining GDP and HDI had a positive and significant influence on deforestation, while population and metal mines showed no significant effect. Non-metallic mineral mines had the strongest impact on increased deforestation, and provinces with high mining productivity spatially tended to experience wider forest destruction. **Conclusions:** These findings emphasize the importance of integrating extractive economic policies with environmental protection so that development does not come at the expense of ecological sustainability.

Keywords: Deforestation; Extractive Economy; Geo-Map Orange Data Mining; Mineral Mining; Panel Data Analysis

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INTRODUCTION

Sustainable global development in the context of natural resource management has a very important role in achieving the Sustainable Development Goals (SDGs) (Shi et al., 2019). The 13th (Climate Action) and 15th (Life on Land) SDGs emphasize the importance of preserving the environment, including the protection of forests and biodiversity(Petrova, 2023). On the other hand, the global economy's need for strategic raw materials, especially from the mining sector, continues to increase, in line with the transition to green energy and the development of the technology industry. This condition creates a paradox between the exploitation of mineral resources and environmental conservation efforts (Flórez et al., 2022). Indonesia, as one of the countries with the largest mineral resource wealth in the world, is located in the midst of tensions between economic development and environmental conservation. The country has reserves of metallic minerals such as nickel, copper, gold, and tin, as well as non-metallic minerals such as coal, quartz sand, and limestone (Asnawi et al., 2024). The Government of Indonesia encourages downstream mining to increase added value and economic independence through the development of smelters and increase the export value of processed commodities (Gasni & Mulyadi, 2022). However, this economic growth stemming from the mining sector is accompanied by a significant increase in the rate of deforestation in many areas, especially in areas with high mining concentrations (Meutia et al., 2023).

Data shows that at the national level, the mining sector's contribution to the Gross Domestic Product (GDP) has continued to increase in the past decade. Several provinces, such as East Kalimantan, Papua, Southeast Sulawesi, and North Maluku, recorded high GDP in the mining sector, both from metallic and non-metallic minerals (Lieu & Ngoc, 2023). At the same time, these provinces are also facing ecological pressures in the form of drastic reductions in forest cover (Eddy et al., 2021). Other provinces such as South Sumatra, Bengkulu, and West Nusa Tenggara also show a similar trend with the dominance of non-metallic mining that extends to protected forest areas. At the regional level, the distribution of mining potential shows an interesting spatial pattern. Metal minerals dominate the eastern region of Indonesia, while the western region is more dependent on non-metallic mines (Widjanarko & Gultom, 2024). Each province has unique characteristics, which are influenced by geographical conditions, economic structure, population number, and achievements in the Human Development Index (HDI). These factors indirectly affect the level of pressure on forest land as well as the ability of regions to manage the environmental impacts of mining activities (Li et al., 2024).

Extractive economic activities, especially in the mining sector, serve as a major economic driver in many developing regions (Warsito, 2020). However, these activities also put significant pressure on the environment, especially in the form of reducing forest cover. In the context of mining, there are two main categories: metal mines and non-metallic mines, which exhibit different characteristics of exploitation as well as ecological impacts. Metal mining, including gold, nickel, and copper, typically operates on a large scale and is often located in primary forest areas (Marame et al., 2023). This activity causes deforestation directly through land clearing, as well as indirect deforestation due to the development of supporting infrastructure such as access roads and settlements. As an illustration, nickel mining activities in Sulawesi and North Maluku since 2020 show a strong link with forest cover loss in the region (Ranjan & Gorai, 2024). Although non-metallic mines such as limestone, sand, and clay operate on a relatively small scale, their impact on local ecosystems cannot be ignored. Recent research shows that these activities can lead to habitat fragmentation, degradation of

soil quality, and increased risk of erosion, especially in areas with weak spatial regulation (Sabdaningsih et al., 2023). In addition, many non-metallic mines are not officially registered, so their environmental impact tends to be less systematically recorded.

The environmental impact caused by mining activities is greatly influenced by the management of natural resources at the local level. Regional autonomy gives local governments the freedom to regulate mining permits, which in turn affects the consistency of environmental supervision (Aurellia et al., 2021) . Research conducted by (Komasi et al., 2022) shows that provinces with weak institutional capacity tend to experience higher rates of deforestation despite their relatively small economic contribution from the mining sector. Previous studies rarely distinguish the impacts of metal and non-metal mining on deforestation. Empirical evidence using regional panel data remains limited, particularly in Indonesia. Yet, recent literature suggests that the two mining types differ in environmental scale and mechanism. Their impact also depends on regulation, regional governance, and global market demand. Therefore, evaluating their relative contributions across regions and time is crucial. A combined sectoral–spatial approach is essential to support sustainable natural resource management policies.

This study aims to analyze the relationship between the existence of metallic and non-metallic mineral mines and deforestation in Indonesia, taking into account supporting variables such as the mining sector's GDP, population size, and HDI. Three approaches were used in this study. First, the Tree Viewers method was used to trace the structure of the influence of mine existence on deforestation and regional economic growth. Second, a panel regression model estimation was carried out to measure the influence of independent variables on deforestation rates quantitatively. Third, a Geo Map approach is used to visualize spatial patterns and variable distribution, including the identification of provinces with the highest pressure on forest land. With this combinatorial approach, it is hoped that research can contribute to formulating more sustainable natural resource-based regional development policies, as well as strengthening the integration between economic and environmental aspects in achieving the SDGs in Indonesia.

METHODS

This study applies a quantitative approach with a panel data design, combining decision tree analysis, panel regression, and geo-map-based spatial analysis to examine the relationship between the mineral mining sector and deforestation in Indonesia.

Study design and setting

This study applies a quantitative approach with a panel data design, observing 34 provinces in Indonesia during the period 2020 to 2024. The purpose of this study is to analyze the impact of the mineral mining sector, both metallic and non-metallic, on deforestation, considering supporting variables such as the mining sector's Gross Regional Domestic Product (GDP), population, and the Human Development Index (HDI).

Population, samples and sampling

The population of this study consists of all 34 provinces in Indonesia. All provinces were included as the study sample and observed annually over five years (2020–2024), resulting in a balanced panel dataset of 170 observations (34 provinces × 5 years). No

provinces were excluded, as the study relies on complete secondary data covering all provinces for the variables of interest: annual deforestation, mining-sector GDP, population, the Human Development Index (HDI), and dummy variables for the presence of metal and non-metal mines.

Instruments and criteria

As this study relies on secondary data rather than a survey instrument, the variables and their official sources are summarized in Table 1.

Table 1. Variables and data sources.

No	Variable	Source
1	Annual deforestation (Ha)	Global Forest Watch (GFW); Statistics Indonesia (BPS)
2	Mining sector GDP (trillion Rp)	Statistics Indonesia (BPS), per province
3	Population	Statistics Indonesia (BPS)
4	Human Development Index (HDI)	Statistics Indonesia (BPS)
5	Metal and non-metal mine dummy	Ministry of Energy and Mineral Resources (ESDM); publications of BPS and the Ministry of Industry
6	Provincial geographical coordinates	Spatial compilation of national geographic sources

Procedure and data collection

Data were compiled from official government and research institutions, including Global Forest Watch (GFW), Statistics Indonesia (BPS), and the Ministry of Energy and Mineral Resources (ESDM), and merged into a single balanced panel dataset covering 34 provinces from 2020 to 2024.

Statistical analysis

To answer the research questions, three complementary analytical approaches were used, implemented with the help of Orange Data Mining software for visual exploration and spatial mapping, as well as EViews for panel regression processing. Tree Viewers Analysis. This method was applied to investigate the structure of relationships between variables and to identify the combinations of factors with the most influence on deforestation. Decision tree modelling was carried out using the CART (Classification and Regression Tree) algorithm in Orange Data Mining, following Decision Tree Theory, in which the target variable (deforestation) is predicted through repeated separation of predictor variables based on "impurity" criteria such as variance reduction or the Gini index (Czech et al., 2017). This technique is particularly effective for understanding non-linear structures and interactions between variables in a format that is easily interpreted visually. Panel regression was used to test the relationships between variables quantitatively over five years of observation, applying the Random Effects Model (REM) approach, which was selected based on the results of the Fixed Effects test and the limitations of the data structure (dummy variables that are static over time). The regression equation used is as follows:

$$DEFLN_{it} = \alpha + \beta_1 GDRB_{it} + \beta_2 POPLN_{it} + \beta_3 HDI_{it} + \beta_4 Dmetallic_{it} + \beta_5 Dnonmetallic_{it} + \varepsilon_{it} \quad (1)$$

where DEFLN is the area of land experiencing deforestation, GDRB is the regional income from the mineral mining sector, HDI is the human quality-of-life index for each province, Dmetallic is a dummy variable coded 1 for provinces with metal mineral mining and 0 otherwise, and Dnonmetallic is a dummy variable coded 1 for provinces with non-metallic mineral mining and 0 otherwise. Spatial Analysis: Geo Map (Orange Data Mining). Spatial analysis was carried out to map the distribution of deforestation, mining-sector GDP, and the existence of metal and non-metal mines, using the Geo Map widget in Orange Data Mining, where the data are converted into a spatial format based on predetermined coordinate points (latitude and longitude of provinces) (Ratnadewati et al., 2025). Visualization in the form of a thematic (choropleth) map helps identify geographical patterns and spatial relationships between provinces, strengthening the interpretation of the regression and decision-tree results.

Ethical considerations

This study relies entirely on secondary, publicly available data obtained from official government and institutional sources (Global Forest Watch, Statistics Indonesia, and the Ministry of Energy and Mineral Resources). As the study did not involve human or animal subjects or primary data collection, formal ethical clearance was not required.

RESULTS

Deforestation in Indonesia is one of the crucial issues that remains an important topic of discussion for the government and the public (Parsch et al., 2025). One of the drivers of large-scale deforestation is the expansion of land for mineral mining. The areas with the largest deforestation are located on several islands, namely Kalimantan, Papua, and northern Sumatra, as shown in the distribution map in Figure 1.

Figure 1. Map of the distribution of deforestation areas in Indonesia, 2020–2024.
Source: Global Forest Watch, processed using Geo-Map (Orange Data Mining), 2025

There are several causes of deforestation in Indonesia, with each of the 34 provinces showing different potentials and patterns. In general, the most relevant issues relate to the social, economic, and productivity dimensions of the mineral

mining sector (Ramadhany et al., 2023). To explore the structure of relationships between variables and identify complex interaction patterns, a decision tree method was applied using the CART algorithm in Orange Data Mining. The resulting visualization shows how the combination of mining-sector GDP, population, and the presence of mineral mines affects the rate of deforestation at the provincial level (Dunlap, 2018).

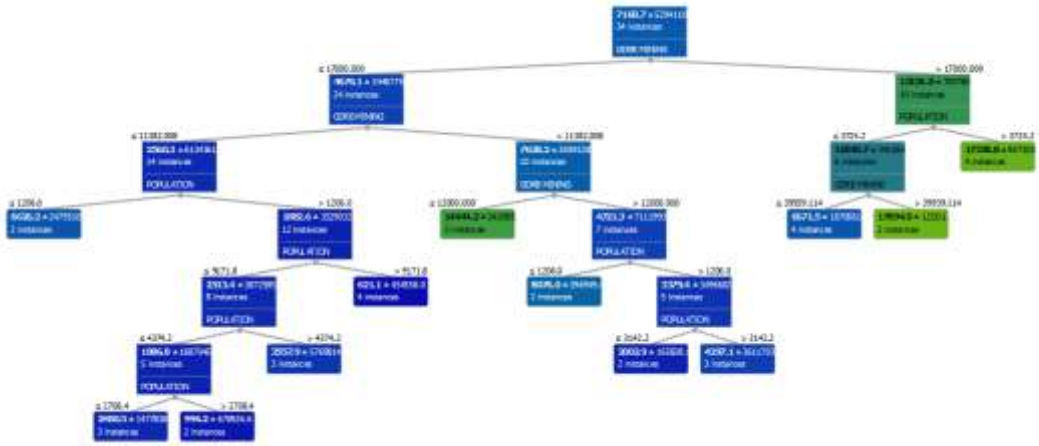

Figure 2. Tree Viewers analysis of factors influencing deforestation.
Source: Various secondary data sources processed using Orange Data Mining, 2025.

The decision tree in Figure 2 shows that the mining-sector GDP variable serves as the main separator (root node) in the classification of deforestation. Provinces with a mining-sector GDP above Rp 17 trillion are consistently located in branches with higher deforestation rates, especially when combined with a large population, indicating that the scale of mining activity is an important factor influencing forest cover loss. Provinces with medium-to-high mining GDP (Rp 11–17 trillion), even without a large population, can still experience deforestation on a significant scale (Warsito, 2020). One node in the tree shows a predicted deforestation value of 14,444 hectares in a province with a below-average population, indicating that mineral mining activity has a major impact on forest ecosystems even without accompanying demographic pressure (Punia & Kumar, 2025). Another node shows that provinces with high mining GDP and a population above 3,700 thousand people experienced extreme deforestation, ranging from 17,358 to 17,694 hectares; spatially, these nodes correspond to provinces such as Papua, East Kalimantan, and Southeast Sulawesi, which are known mining centres for metals (nickel, copper, gold) as well as non-metallic minerals (coal, limestone) (Pratiwi et al., 2021).

The results were further analyzed using panel data regression across the 34 provinces for the period 2020–2024, to determine which social, economic, and productivity factors of mineral mining are associated with the extent of deforestation. The results are presented in Table 2.

Table 2. Panel data regression analysis results.

No	Variable	Coefficient	Probability
1	C	-26.27	0.00
2	GDRB	0.43	0.00
3	Population	-0.20	0.25
4	HDI	-0.33	0.00

5	DMetallic	0.36	0.42
6	Dnonmetallic	7.01	0.00
	R-Squared	0.33	
	Prob (F-Statistic)	0.00	

Source: Secondary data, processed, 2025.

The estimated regression equation (2) is as follows:

$$DEFLN_{it} = -26.27 + 0.43\,GDRB_{it} - 0.20\,POPLN_{it} - 0.33\,HDI_{it} + 0.36\,Dmetallic_{it} + 7.01\,Dnonmetallic_{it} + \varepsilon_{it} \quad (2).$$

The Random Effects Model (REM) was selected based on the results of the Fixed Effects test and the static nature of the dummy variables over time. Mining-sector GDP (coefficient 0.43, significant at 1%), HDI (coefficient −0.33, p = 0.00), and the non-metallic mine dummy (coefficient 7.01, p = 0.00) were statistically significant predictors of deforestation, whereas population (p = 0.25) and the metal-mine dummy (p = 0.42) were not. Spatial analysis of the distribution of mining-sector GDP in Figure 3 illustrates this relationship further. Provinces shown in light-to-orange colours including Papua, East Kalimantan, Central Kalimantan, and North Sumatra show very high levels of mining productivity, with mining-sector GDP exceeding Rp 125 trillion per year (Anisa et al., 2023). These same provinces were also recorded as having the highest deforestation rates in the preceding regression and decision-tree analyses. In contrast, provinces with low mining-GDP contributions such as DKI Jakarta, DI Yogyakarta, Bali, and parts of Central and West Java show much lower rates of deforestation (Silva et al., 2023).

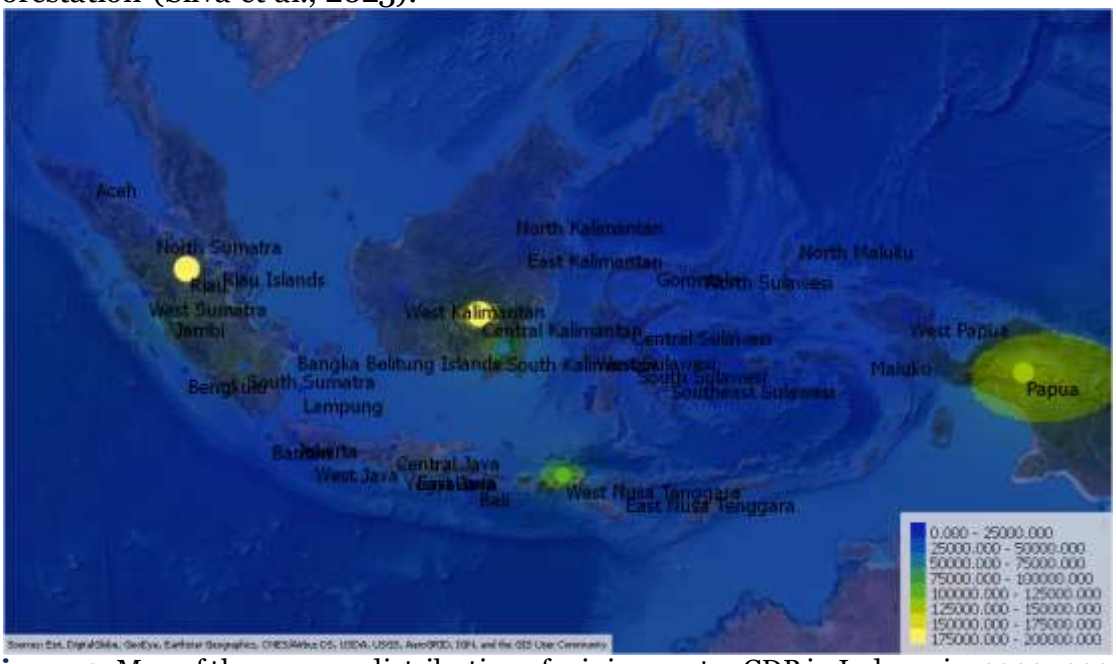

Figure 3. Map of the average distribution of mining-sector GDP in Indonesia, 2020–2024.
Source: BPS, processed using Geo-Map (Orange Data Mining), 2025.

The panel regression results also show that the Human Development Index (HDI) has a positive and significant relationship with deforestation, with a coefficient of 0.33 (p = 0.00): each one-point increase in a province's HDI is associated with an average increase in deforestation of about 0.33% on a logarithmic scale. Spatially, the HDI distribution map in Figure 4 shows that provinces such as East Kalimantan, Southeast Sulawesi, and West Papua, which have moderate-to-high HDI, were also recorded among the areas with high deforestation rates. In contrast, provinces such as Jakarta, Yogyakarta, and Bali show high HDI but low deforestation rates.

Figure 4. Average Human Development Index (HDI) map of Indonesia, 2020–2024.
Source: BPS, processed using Geo-Map (Orange Data Mining), 2025.

The regression results further show that areas with non-metallic mineral mines had a sevenfold greater difference in deforestation potential compared with other areas (coefficient 7.01, p = 0.00), the largest effect among all variables tested. The distribution map in Figure 5 shows that provinces with active non-metallic mines including South Sumatra, South Kalimantan, East Kalimantan, Papua, and Southeast Sulawesi are widely spread across almost all major islands, from Sumatra to Papua (Abbas et al., 2023; Azzam et al., 2022), while provinces without non-metallic mining activity are limited to a small number of areas in Java, such as Yogyakarta.

Figure 5. Map of the distribution of areas with non-metallic mineral mines in Indonesia, 2020–2024.
Source: Secondary datasets, processed using Geo-Map (Orange Data Mining), 2025.

By contrast, the dummy variable representing the existence of metal mineral mines did not have a statistically significant effect on deforestation (coefficient 0.36, p = 0.42). As shown in the distribution map in Figure 6, metal mines are concentrated in specific, localized areas such as Halmahera, Konawe, Mimika, and Weda Bay, and almost all provinces in Indonesia have at least one type of metal-mining activity, with only Yogyakarta and DKI Jakarta showing none.

Figure 6. Map of the distribution of areas with metal mineral mines in Indonesia, 2020–2024.
Source: Secondary datasets processed using Geo-Map (Orange Data Mining), 2025.

DISCUSSION

Although the decision tree does not display the metal and non-metal mine dummies explicitly as separator nodes owing to their static nature within the five-year panel the contribution of mining type is implicitly reflected through the mining-sector GDP value, which itself embeds the output of both metal and non-metallic commodities (Zhu et al., 2024). Based on spatial and economic interpretation, non-metallic mines such as coal are widespread in Kalimantan and South Sumatra, both high-deforestation regions, while metal mines are concentrated in Papua, Sulawesi, and North Maluku, which are likewise high-risk areas for forest cover loss (Hasibuan & Rukiah, 2023). The decision tree therefore not only describes a linear relationship between variables but also points to the complexity of the mining sector's influence across both metal and non-metal types in shaping environmental pressure.

The regression results reinforce the view that human economic activity, particularly in the mineral mining sector, tends to open new land through deforestation (Ranjan & Gorai, 2024): when all independent variables are held at zero, the model still predicts a substantial baseline level of deforestation. Beyond mining-sector GDP itself, the Human Development Index and the presence of non-metallic mines also emerged as significant explanatory factors (Hidayat et al., 2018), indicating that the pressure on Indonesia's forests stems from an interconnected set of economic and social drivers rather than mining activity in isolation. The positive relationship between mining-sector GDP and deforestation is consistent with the broader literature on extractive economies: the greater the contribution of the mining sector to a region's economy, the higher the pressure on the sustainability of forest ecosystems (Suryani et al., 2023). This pattern aligns with previous findings that extractive activities tend to drive land expansion for exploration, mining operations, infrastructure, and downstream industrial development such as smelters (Ministry of Energy and Mineral Resources, 2015). The spatial concentration of both high mining-sector GDP and high deforestation in provinces such as Papua, East Kalimantan, Central Kalimantan, and North Sumatra demonstrates a real linkage between extractive economic centres and areas experiencing significant forest degradation, while low-mining-GDP provinces such as DKI Jakarta, DI Yogyakarta, and Bali with economies oriented toward services rather than extraction show correspondingly lower deforestation. This underscores the importance of integrating economic growth with environmental protection: local governments need stricter mining-area zoning policies, enforcement of reclamation obligations alongside sustainable mining practices, and closer coordination between regional planning, environmental, and extractive-industry agencies(Consolee et al., 2025). Without ecosystem-based management, mining activity risks worsening national deforestation rates and moving Indonesia further from its Sustainable Development Goals commitments, particularly SDG 13 (Climate Action) and SDG 15 (Life on Land).

The positive and significant relationship between HDI and deforestation is a more counter-intuitive finding, since human development is generally associated with improved quality of life and governance. The results instead highlight a paradoxical side of development: higher human development can coincide with greater environmental pressure on forest areas, particularly where rising incomes and education drive settlement expansion, infrastructure development, and land demand for industry, including mining and energy (Hacıalioğlu & Türkoğlu, 2026). This suggests that HDI gains not accompanied by stronger environmental governance may, in practice, increase resource consumption and land conversion. The contrasting pattern in Jakarta, Yogyakarta, and Bali high HDI but low deforestation, likely

reflecting already-minimal forest cover and service- and manufacturing-oriented economies shows that high HDI need not come at the expense of forest ecosystems if supported by environmentally sound spatial planning, forest-area protection, and control over land conversion in resource-rich provinces (Syukri et al., 2024). Achieving this balance calls for a cross-sectoral approach in which education, health, and economic policy work synergistically with forestry and environmental management to produce growth that is both inclusive and sustainable.

The particularly strong effect of non-metallic mines is consistent with the argument that activities such as coal, limestone, quartz-sand, and clay extraction are major drivers of forest cover loss in Indonesia (Marame et al., 2023). Unlike metal mines, which tend to concentrate in specific regions, non-metallic mines are more geographically dispersed and often operate at an extensive scale to meet energy and building-material demand which likely explains why their spatial footprint (Figure 5) covers almost every major island, and why public and policy attention, often focused on strategic metal commodities such as nickel and gold, may be under-weighting the more evenly distributed and statistically consistent ecological impact of non-metallic mining (Mervine et al., 2025). This points to a need for strengthened supervision and regulation of non-metallic mining activities, including licensing, mining-zone control, and post-mining reclamation and reforestation obligations.

The non-significant effect of the metal-mine dummy can plausibly be explained by two factors. First, metal mines tend to operate in highly specific and localized areas (e.g., Halmahera, Konawe, Mimika, and Weda Bay), so their ecological impact is concentrated at the micro or district level rather than manifesting clearly at the provincial level used in this analysis. Second, many metal mines operate under stricter regulatory oversight as strategic-sector operations, potentially limiting the extent of direct forest damage compared with the more widespread and less tightly regulated non-metallic mining sector (Sabdaningsih et al., 2023). This indicates that the mere presence of metal mines is not, by itself, a reliable indicator of provincial-level deforestation pressure; a more granular approach for example, at the district or mining-concession level, with production-volume data rather than administrative presence alone would likely provide a more accurate picture of the ecological impact of metal mining. Overall, these findings should be interpreted in light of the study's scope: the analysis is conducted at the provincial level using a five-year panel, which may mask within-province heterogeneity and cannot fully capture the more localized dynamics of metal mining or the administrative and enforcement gaps affecting unregistered non-metallic mines. Future research using district-level or mining-concession-level data, and longer time series, would help to refine these findings.

CONCLUSIONS

This study aimed to analyse the impact of the existence and productivity of the mineral mining sector on deforestation in 34 provinces in Indonesia during 2020–2024. By integrating panel data regression, decision tree visualization, and geographic map-based spatial analysis, the study provides a comprehensive picture of the relationship between mining activity and forest cover loss at the regional level. The regression results show that mining-sector productivity, represented by mining-sector GDP, has a positive and significant influence on deforestation: the greater the sector's contribution to the regional economy, the higher the rate of deforestation. The Human Development Index (HDI) also shows a significant influence, indicating that human development not balanced with stronger environmental governance can increase pressure on forest areas. In contrast, population and the metal-mine dummy did not

show significant effects, suggesting that ecological impact does not necessarily stem from demographic pressure or the mere presence of metal mines, but is more strongly influenced by land-use intensity and governance factors. The most striking finding is that the presence of non-metallic mineral mines has a strong and significant influence on deforestation, reinforced by spatial distributions showing these mines widespread across almost all provinces especially Kalimantan, Sumatra, Sulawesi, and Papua making them one of the major contributors to forest ecosystem degradation at the national scale. A more in-depth spatial view shows that areas with high deforestation rates generally also have high mining-sector GDP and active non-metallic mines, whereas provinces with high HDI and urban character, such as Java and Bali, show low deforestation rates indicating that economic and human development supported by sound environmental policy can still reduce ecological damage. This study therefore emphasizes the importance of integrating extractive economic policy with environmental protection, and the need to evaluate development models that rely heavily on natural-resource exploitation as a primary pillar of growth. Spatial approaches combined with cross-provincial panel data can serve as valuable tools for more sustainable development planning in Indonesia.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Not applicable.

DECLARATION OF ARTIFICIAL INTELLIGENCE USE

We hereby confirm that no artificial intelligence (AI) tools or methodologies were utilized at any stage of this study, including during data collection, analysis, visualization, or manuscript preparation. All work presented in this study was conducted manually by the authors without the assistance of AI-based tools or systems.

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