Jurnal Manajemen Hutan Tropika, *30*(1), 97–106, April 2024
EISSN: 2089-2063
DOI: 10.7226/jtfm.30.1.96

Scientific Article
ISSN: 2087-0469

A Changing Landscape: Exploring the Relationship between Clean and Clear Status Policy, Coal Mining, and Deforestation

Achmad Prabu Widjanarko[1], Yohanna Magdalena Lydia Gultom[2]

[1]Graduate Progam of Planning and Development Policy, Faculty of Economics and Business, Universitas Indonesia, Campus Salemba, Jakarta, Indonesia 10430
[2]Department of Economics, Faculty of Economics and Business, Universitas Indonesia, Campus Salemba, Jakarta, Indonesia 10430

Received August 27, 2023/Accepted January 5, 2024

Abstract

Coal plays a crucial role in energy generation in developing nations and serves as a vital source of power amidst growing energy demands. However, coal mining often acts as a primary driver of deforestation and poses significant environmental challenges. Indonesia, a country with extensive forest areas and a significant coal producer, has implemented a Clean and Clear status policy to address regional and administrative issues related to mining permits. This study aims to assess the impact of this government permit for coal mining in forest areas using the fixed effect panel data method, offering insights into the relationship between coal mining activities and deforestation trends. The analysis focused on the period from 2010 to 2019 and covered 110 regencies in Indonesia, providing a comprehensive understanding of the spatial and temporal dynamics of forest loss. The estimation findings indicated a negative correlation between the areas allocated for coal mining concession permits and forest areas, underscoring the need for stringent regulations and effective land management practices. Therefore, it is recommended that the Clean and Clear status policy not only be applicable during the permit granting phase, but also prioritize post-mining periods to ensure the completion of land reclamation activities.

Keywords: *permit, forest area, fixed effect panel, mining, coal*

**Correspondence author, email*: *achmadprabu@gmail.com*

Introduction

Deforestation refers to the loss of forested areas caused by land conversion or natural disasters (Sunderlin & Resosudarmo, 1997; Landry & Matthews, 2016). It occurs in the tropical forest regions of developing countries, including Indonesia (FAO, 2020). According to Fünfgeld (2020), coal mining activities can contribute to deforestation, primarily because of the extensive land requirements of mining methods such as open-pit mining (Gao et al., 2021). This method enables mining operations in areas with shallow depths or those limited to the soil surface (Trigg & Richard Dubourg, 1993).

To address the deforestation caused by the mining sector, the Indonesian government implemented the Clean and Clear status policy. The Clean and Clear policy is a designation conferred by the Directorate General of Mineral and Coal, and is subsequently embedded in the form of a certificate for Mining Business Licenses that have met administrative, spatial, and environmental requirements. The Clean and Clear policy was initially introduced by the Ministry of Energy and Mineral Resources Regulation Number 2 of 2013. Essentially, this regulation mandated the Directorate General of Mineral and Coal to oversee Mining Business Licenses at the regional level, ensuring that they fulfil comprehensive business feasibility requirements. Meanwhile, Minister of Energy and Mineral Resources Regulation Number 43 of 2015 represents an amendment to the previous regulation, specifying that Clean and Clear status would be granted in the form of a certificate. The process of reconciliation and re-evaluation of the completeness of requirements for Mining Business License holders conducted before 2015 was used as the basis for revoking Mining Business Licenses in 2015. The completeness of the environmental requirements outlined in this regulation is still within the context of forest land utilization governed by Law Number 41 of 1999 Article 38 Paragraph 4, which fundamentally prohibits the use of forest land for open-pit mining activities.

The decentralization of mining policy in Indonesia is perceived as advantageous, as local governments are better positioned to manage regional resources because of their proximity to the central government (Saputra & Mahmudi, 2012). In general, the expansion of coal mining decentralization is determined by the demand for domestic coal-based electricity generation and Indonesia's main export commodities. The utilization ratio of coal as the primary energy supply is the largest, accounting for 33% of the energy mix, whereas coal consumption in 2025 is estimated to reach 132 million tons. In addition, Adiatma et al. (2018), PLN's coal consumption of PLN is expected to

EISSN: 2089-2063
ISSN: 2087-0469
DOI: 10.7226/jtfm.30.1.96

increase by 44%. These high consumption levels, however, have both social and environmental implications. One of these implications is that thousands of mining concession permits were issued by local governments, namely regencies and cities, between 2001 and 2019 before the enactment of the Minerba Law in 2020. Nevertheless, in the implementation of this decentralization policy, overlapping mining and forest areas still exist (KPK, 2018), requiring the policy to be re-validated.

Revalidating this policy is crucial, as one of its objectives is to preserve forested areas. Forest areas consist of vegetation, which plays a vital role in maintaining the water cycle, soil density, and soil fertility (Ginoga et al., 2005). They also serve as carbon sinks, preventing the release of carbon into the environment (Norberg, 1999). Deforestation in Indonesia led to the release of 924,853 CO_2e carbon emissions in 2019, which is equivalent to 50% of the total greenhouse gas emissions that year (KLHK, 2021). In addition to carbon emissions, the loss of forested areas also results in the deprivation of opportunities to convert carbon dioxide into oxygen. Numerous studies have been conducted on the implementation of governance permits, which have yielded diverse outcomes. Long (1975) suggests that companies tend to exploit high-risk commodities excessively. Exploitation beyond permitted boundaries or even outside designated areas occurs because of the risky nature of mining operations (Gu et al., 2010; Konicek & Waclawik, 2018; Li et al., 2021). On a different note, Bohn and Deacon (1997) focus on the weak licensing aspects from the company's perspective, leading to exploitation falling short of set targets.

Empirical studies on policies aimed at reducing deforestation in developing countries have yielded mixed results. Castro-Nunez et al. (2020) concluded that policies to reduce deforestation targeting Colombia's main plantation commodities did not work effectively because they were not supported by data at the local level. Rodríguez-de-Francisco et al. (2021) also found that the implementation of REDD in Colombia did not run optimally because of its focus on indigenous forests, whereas deforestation in that country is actually the result of an imbalance of power, corrupt regional governments, and cattle intensification policies that can only be effective when market conditions are at a saturation point (Müller-Hansen et al., 2019). Rahman and Islam (2021), in their research in Bangladesh, showed how the policy of establishing protected forests did not reduce the rate of deforestation; instead, it reduced the protected forests by as much as 37%. Others have argued that policies on the efficient use of fertilizers and seeds can reduce deforestation rates because fertile soil reduces the clearing of agricultural land (Ngoma et al., 2021).

While some studies show how policies in agriculture and plantations can also reduce deforestation, mining activities are still one of the dominant factors for deforestation, and the policies that regulate mining areas with government permits are still unclear regarding their impact on reducing deforestation (Laing, 2019; Siqueira-Gay et al., 2020; Vuola, 2022). Thus, the purpose of this study was to determine whether the application of the Clean and Clear status policy has been effective in reducing deforestation.

Methods

Time and location This study utilized secondary data from 2010 to 2019 in 110 districts and cities across Indonesia. Astronomically, Indonesia is located between N6°08' and S11°15' latitude and between E94°45' and E141°05' longitude, bordered by Malaysia, Timor-Leste, and Papua New Guinea. Indonesia is also bordered by the Indian Ocean to the South and the Pacific Ocean to the North, facilitating coal shipments using barges. In 2019, Indonesia recorded coal exports of 454.5 million tons, equivalent to 25.7% of global exports (BP, 2020). These exports were primarily directed toward India, China, and South Korea. Coal production in 2019 reached 616 million tons, accounting for 7.5% of global coal production (ESDM, 2021).

Data collection and analysis This study utilized land area data obtained from the Ministry of Environment and Forestry of Indonesia (KLHK) and the Ministry of Energy and Mineral Resources of Indonesia (ESDM). The data from the Ministry of Environment and Forestry represent annual land cover data, whereas the data obtained from the Ministry of Energy and Mineral Resources comprises mining business license areas for both coal and other minerals that were still active from 2010 to 2019. The following data (Table 1), presented in the form of descriptive statistical tables, were used in this study.

The mining permit data exclusively include companies with production operation permits. In contrast, the forest area data comprise both primary dryland forest areas, which are forests recognized as undisturbed by human activities, and secondary dryland forest areas, which are forests acknowledged to have undergone human disturbances, such as logging indications.

Empirical model This research utilizes an empirical model to enhance our understanding of the influence of the Clean and Clear policy on mining activities and deforestation. The empirical model necessitates two categories of variables, independent variables and dependent variables, as shown in Equation *[1]*.

$$KH_{it} = \beta_0 + \beta_1 BB_{1,it} + \beta_2 RIUP_{2,it} + \beta_3 MN_{3,it} + \beta_6 PMK_{6,it} + \beta_7 PTN_{7,it} + \beta_8 PKN_{8,it} + \delta_t + \varepsilon_{it} \qquad [1]$$

note: *KH* = forest area, *BB* = coal area, *RIUP* = the ratio of IUP mining area to the total mining land area, *MN* = mineral mining land area other than coal, *PMK* = residential area, *PTN* = agricultural area, *PKN* = plantation area, δ_t = dummy years since policy enactment, ε_{it} = variable error, $\beta_0, \beta_1, \ldots, \beta_8$ = constant.

In the empirical model, the dependent variable, KH_{it}, represents the extent of forest areas affected by the independent variable, which is the area of coal mining. The symbol "i" denotes districts or cities, and "t" represents the data period from 2010 to 2019. To minimize potential estimation biases, the empirical model incorporates the following control variables: *RIUP*, *MN*, *PMK*, *PTN*, and *PKN*. The *RIUP* variable serves as a control for the decentralization policy in mining, using the ratio of mining permit (IUP) area to the total mining area for each year.

Jurnal Manajemen Hutan Tropika, *30*(1), 97–106, April 2024
EISSN: 2089-2063
DOI: 10.7226/jtfm.30.1.96

ISSN: 2087-0469

Table 1 Statistic descriptive

Variable	Obs	Average	Std. deviation	Min	Max
Dependent					
Forest area	1,100	311,596.400	609,735.800	1,000	3,783,000.0
Independent					
Coal areas	1,100	19,592.750	47,792.370	0	375,262.9
Control	1,100				
IUP ratio	1,100	0.548	0.486	0	2.0
Other mineral area	1,100	5,125.651	18,705.020	0	306,846.0
Residential area	1,100	3,917.273	4,575.220	0	28,000.0
Plantation areas	1,100	68,773.180	120,250.600	0	1,118,000.0
Agricultural areas	1,100	156,815.500	174,208.000	1,000	983,000.0

Additionally, the study includes the *MN* variable, representing the area of other mining permits, as it assumes that forest land conversion occurs when land is opened for other mining commodities. The *PMK* variable acts as a control for the settlement extent and serves as a proxy for land conversion into residential areas. This variable acknowledges the substantial conversion of forest land into settlements owing to population density, where populations near forest areas convert them into residential spaces (Nazir & Ahmad, 2018). Another control variable, *PTN*, represents agricultural land conversion. It combines dryland agricultural areas and mixed dryland areas, including terraced fields and mixed plantations. Expanding agricultural land is often associated with forest land conversion (Abman & Carney, 2020a, 2020b; Franco-Solís & Montanía, 2021; Kazungu et al., 2021; Mullan et al., 2021). The study also considered the plantation area as a control variable. The plantation sector, including palm oil, contributes significantly to the country's GDP and meets international consumer demand. While the plantation industry stimulates regional and sectoral economies and generates foreign exchange, it requires extensive land and often overlaps with forested areas (Kamim, 2018). Consequently, forest conversion and deforestation occur because of the unavoidable intersection between palm oil plantations and forested areas. The model includes a dummy variable (δ_t) to assess the impact of the decentralization policy on the granting of coal mining permits, which represents the years since the implementation of the policy in 2015. Furthermore, the model assumes the presence of ε as a representational variable that influences the dependent variable, but is not explicitly included in the model.

Estimation strategy This study employs a panel data model to estimate the correlation between the independent and dependent variables. The panel data method is commonly used to examine the impact of independent variables on dependent variables and has been widely applied in various studies (Huang et al., 2019; Lee et al., 2019; Feng et al., 2020; Akram et al., 2021; Kassouri et al., 2021; Ji et al., 2022). The residual represents external factors that influence the dependent variable but are not included in the model. This study utilizes panel data, which consists of cross-sectional and time-series data. The fixed-effect panel data model allows for different intercepts across subjects, whereas the slopes of these subjects remain constant over time (time invariant). In other words, this model assumed a consistent slope for each subject. To distinguish between subjects, the model employs dummy variables derived from the cross-section. However, omitting variables that impact the model can lead to estimation bias, known as omitted variable bias (OVB) (Gujarati & Porter, 2009). To address this concern, a robustness check, called the model strength test, can be conducted (Peng et al., 2021). This test helps evaluate consistency by progressively adding control variables to the model (Lu & White, 2014). In this study, the model strength test was performed by initially modelling the dependent variable with the primary independent variable and subsequently incorporating other control variables one by one.

Results and Discussion

The background to the Clean and Clear status policy is government mining permits or IUP. This regulation requires mining companies to provide administrative documents related to mining permits. This includes regional coordinates and maps, documents to guarantee no overlap with forest areas or other mining commodities, and other documents, such as financial-related obligations and environmental impact analysis (AMDAL). In 2015, the Central Government conducted a reconciliation process under the Ministry of Energy and Mineral Resources (ESDM) Regulation Number 43 of 2015, which regulates the procedures for granting IUP.

There are two criteria for the IUP i.e., a) mining areas that meet the requirements with complete documents are given the CnC (Clean and Clear) IUP status and b) for those with incomplete documents are given non-CnC IUP status. Furthermore, for the existing IUP before the implementation of the regulation, there will be an evaluation. If IUP are classified as non-CnC, their permits will be revoked unless they comply immediately with the applicable provisions.

The outcomes derived from the regression of the fixed-effects panel data analysis in Table 2 reveal that the coal area variables exhibit a negative impact. The regression results indicate that the constructed model is not statistically significant (p-value > 0.05), with an R^2 of 0.12, suggesting that the model explains only approximately 12% of the variation in the dependent variable. The regression coefficient (-0.0587) showed a negative relationship between the independent and dependent variables, but the value was small. Therefore, the independent variable used did not have a significant influence on the dependent variable, which is consistent with the findings of Kartikasari

Jurnal Manajemen Hutan Tropika, *30*(1), 97–106, April 2024
EISSN: 2089-2063
DOI: 10.7226/jtfm.30.1.96
Scientific Article
ISSN: 2087-0469

et al. (2018), who employed Landsat satellite imagery across various time frames to assess the expansion of coal mining areas within forested regions. Their research concluded that coal mining contributes to deforestation or exhibits a negative association with forested areas owing to land conversion. The large number of coal mining permits is closely linked to the enactment of regional autonomy policies, which entails the delegation of certain policies from the central government to local governments (Solechah, 2012).

To comprehend the effects of decentralization policies on mining permits, the model incorporates time fixed effects control variables, starting from the year when the Clean and Clear IUP status, which involves the participation of local governments (assessed by the governor), was implemented. The revocation of IUP permits, resulting from the governor's evaluation, began to be enforced in 2015, necessitating companies to fulfill various regional and administrative requirements to attain such status. This Clean and Clear status also ensures that unregulated open-pit mining areas do not intersect with forested areas. Nevertheless, the empirical estimation results revealed a negative correlation between the size of coal permits and the extent of forested areas. A negative correlation may indicate that an increase in the number of more intensive mining permits has the potential to contribute to changes in forest area. However, it should be noted that this correlation does not directly indicate a cause-and-effect relationship. Other factors, such as environmental policies, deforestation mitigation efforts, or changes in natural conditions, can also influence the dynamics of the relationship between mining permits and forest area. The large number of coal mining permits, often a consequence of regional autonomy policies, presents a policy challenge. Therefore, a careful examination of the effectiveness of a Clean and Clear status in preventing the intersection of unregulated open-pit mining with forested areas is crucial. In light of our research, policymakers must consider the potential long-term environmental implications of the current trajectory. The observed negative correlation prompts the need for targeted policies, possibly revisiting the Clean and Clear implementation, and enhancing measures to mitigate deforestation associated with coal mining activities. This holistic approach, informed by our empirical findings, can guide future interventions and ensure sustainable development, while preserving critical forest ecosystems.

Additionally, to understand the impact of various types of coal mining permits, the model incorporates the ratio of the mining permit area to the total area of coal permits for each year. The estimation results revealed a positive coefficient of coal mining for the permit area ratio, although this was not statistically significant. This can be attributed to the high demand for coal, which is a major driving factor behind the issuance of coal mining permits. Regarding domestic demand, coal plays a pivotal role in power generation, as indicated in the electricity supply business plan (RUPTL), where coal accounts for 54.6% of the primary energy mix (PLN, 2020). In 2018, coal production reached 557 million tons, with domestic consumption of 115 million tons, while the remaining 557 million tons were exported (DEN, 2019). Domestic coal consumption primarily caters to electricity generation from coal-fired power plants (PLTU). In terms of demand, domestic electricity consumption has witnessed significant growth over a four-year period from 2014 to 2018, increasing by 24% from 812 kWh to 1.021 kWh. It is anticipated that this figure will continue to increase in the coming years. Adiatma et al. (2018) also affirm a 44% surge in coal consumption over the past 15 years.

To investigate the structural break in the impact of mining permit licenses on forested areas from 2010 to 2019, we generated a treatment trend graph. The term 'treatment' refers to the implementation of the Clean and Clear policy, which commenced in 2015. On the X-axis, we designated 0 as 2015, -4 as 2011, and 4 as 2019. A graph depicting these trends is shown in Figure 1.

The graph illustrates a reduction in forest area in Indonesia from 2010 to 2019. Regions embracing coal mining experienced a significant decline, witnessing a drop in forest area from approximately 375,000 to 325,000 within eight years and an alarming loss of 50,000 units. This highlights the adverse impacts of coal mining on Indonesia's

Table 2 Model specifications test

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Coal areas	-0.141*	-0.0868	-0.0806	-0.0812	-0.0604	-0.0587
	(-2.04)	(-1.34)	(-1.33)	(-1.43)	(-0.93)	(-0.90)
Mineral areas		-0.314***	-0.315***	-0.314***	-0.233**	-0.231**
		(-3.84)	(-3.88)	(-3.91)	(-3.20)	(-3.18)
IUP ratio			3332	3327.6	2799.7	2700.1
			(-1.08)	(-1.07)	(-0.93)	(-0.92)
Residential areas				0.0896	0.537	0.54
				(-0.1)	(-0.6)	(-0.61)
Plantation areas					-0.107**	-0.110**
					(-3.27)	(-3.33)
Agricultural areas						-0.00792
						(-0.44)
Constant	314,354.5***	321,768.0***	320,032.6***	319,764.9***	323,547.3***	325,042.8***
	(50.71)	(87.41)	(89.81)	(81.02)	(33.23)	(27.08)
Observation	1,100	1,100	1,100	1,100	1,100	1,100
R^2	0.02	0.099	0.101	0.101	0.127	0.128

The standard errors are in parentheses.
* = p-value < 0.05, ** = p-value < 0.01, *** = p-value < 0.00

Jurnal Manajemen Hutan Tropika, *30*(1), 97–106, April 2024
EISSN: 2089-2063
DOI: 10.7226/jtfm.30.1.96

ISSN: 2087-0469

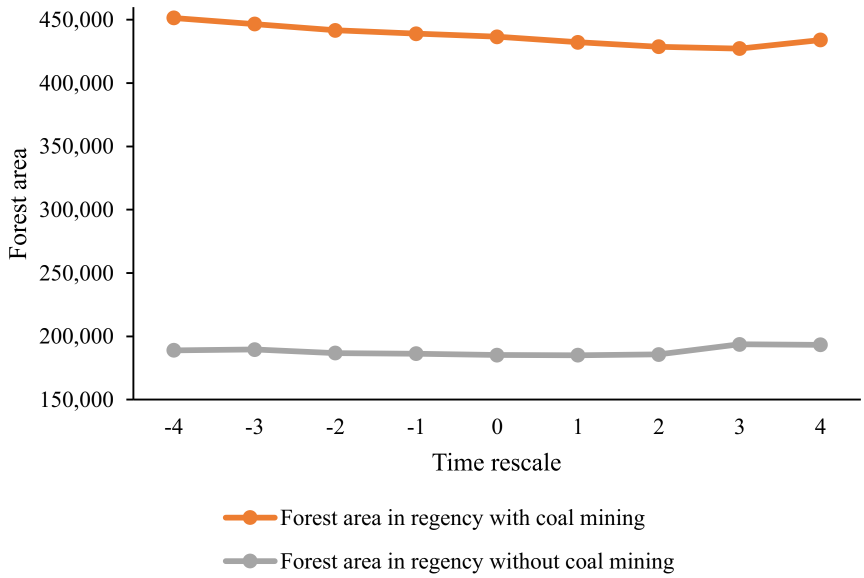

Figure 1 Treatment of Clean and Clear policy to forest in regency with and without coal mining.

valuable forests. In contrast, regions that avoided coal mining showed more favorable outcomes. The forest area decreased from approximately 425,000 to 400,000 during the same period, representing a loss of 25,000 units.

The surge in coal utilization within the energy sector is influenced by various factors, including energy prices and policies. In pursuit of bolstering economic growth, the Indonesian government strives to maintain affordable energy prices by maximizing the utilization of cost-effective coal-based fuels. Affordable energy prices serve as a benchmark to ensure widespread access to electricity for the majority of the population. Simultaneously, Indonesia holds a prominent position as a leading global coal exporter, catering to countries such as Japan, India, Korea, and China (BP, 2020). The government has generated significant revenue from the coal sector, amounting to IDR31 trillion over the past four years. In 2018, coal production reached 500 million tons (ESDM, 2019). Nevertheless, the escalation in coal production has implications that extend beyond deforestation, impacting communities and the environment through externalities.

Regarding its environmental effects, a study conducted by Jiang et al. (2022) in China revealed that coal mining exerts a detrimental influence on groundwater, whereas research by Li et al. (2022) demonstrated that it contributes to the degradation of soil quality. Additionally, Chong and Collie (2022) indicated that coal mining has adverse health effects. Similar health repercussions resulting from coal mining are observed in Appalachia, as highlighted by Mueller (2022), who emphasized elevated mortality and morbidity rates in mining areas. Another environmental concern stemming from coal mining is the instability of soil and the potential for increased landslide occurrence, both in China (Yang et al., 2022) and Mongolia (Ma et al., 2021). On a social front, mining negatively impacts the land use of local communities (Villén-Pérez et al., 2022) and often leads to conflicts with agricultural land (Li et al., 2021). However, the transformation of forested regions into non-forest areas presents a range of additional concerns, including the heightened emission release into the environment (Zaman, 2022), the depletion of native habitats (Supriatna et al., 2020), and the reduction of carbon storage reserves (Guadalupe et al., 2018).

Furthermore, the coal mining sector employs four methods to release emissions into the environment. First, roads were constructed using forests for exploration purposes. Second, forested land was converted into mining areas. Third, coal is transported from mining sites to the coal-fired power plants. Finally, coal combustion was used for electricity generation. In 2019, the conversion of coal combustion into CO_2 gas amounted to 30 $GtCO_2$ (IEA, 2018). Such substantial emissions contribute to the accumulation of greenhouse gases (GHGs) in the atmosphere, resulting in global warming (Wahyuni & Suranto, 2021) and climate change (Bjornlund, 2010). Additionally, this leads to the depletion of topsoil, organic matter, and vital nutrients in significant quantities (Banerjee et al., 2020).

Forest conversion induces soil degradation, adversely affecting the structure, organic matter, and life of soil organisms. This degradation reduces soil macroporosity, hinders surface infiltration, and increases runoff (Zhang et al., 2021). This disruption alters soil flow patterns and affects soil chemistry and nutrient composition. Rainfall and runoff cause a decline in the soil aggregate stability associated with organic matter, roots, and microorganisms (Chen et al., 2020). This reduction in the binding components makes the soil prone to fragmentation, resulting in smaller particles and surface crusts. Finer particles block the soil pores, diminish porosity, restrict water movement, and increase erosion. The implications of forest conversion on soil degradation bear significant environmental considerations for land use decisions (Wang et al., 2019).

Post-mining practices that prioritize the reclamation of concession areas play a vital role in a company's environmental accountability following exploitation. These practices entail the restoration, arrangement, and

Jurnal Manajemen Hutan Tropika, *30*(1), 97–106, April 2024
EISSN: 2089-2063
DOI: 10.7226/jtfm.30.1.96
Scientific Article
ISSN: 2087-0469

reforestation of the previously exploited concession areas. Neglecting these measures by responsible companies can lead to disruptions in the carbon cycle in the environment. These imbalances not only impact the natural ecosystem but also have ramifications for the socioeconomic welfare of local communities.

The control variables that exhibit a negative correlation with forest area include the size of permits for other mineral mining, agricultural land area, and plantation area. This means that increasing the size of permits for other mineral mining, expanding agricultural land, and the growth of plantation areas are correlated with a tendency toward a decrease in forest area. While these findings reflect a statistical relationship, it is essential to note that correlation does not imply causation; the estimation results indicate that the other mining permit variables have a negative correlation with forest area, with $R^2 = 0.12$, coefficient value = -0.231, p-value < 0.001. This can be attributed to the more equitable distribution of values for other mining permits across the control districts compared with the total area of coal mining permits. Similarly, the agricultural and plantation variables also display a negative correlation with the forest area, with result in plantation, $R^2 = 0.12$, coefficient value = -0.11, p-value < 0.01 and with result in agricultural area, $R^2 = 0.12$, coefficient value = -0.007, p-value > 0.05 This aligns with the initial assumption used in the estimation strategy, suggesting a negative relationship between the agricultural variable and the forest area (Abman & Carney, 2020a, 2020b; Franco-Solís & Montanía, 2021; Kazungu et al., 2021; Mullan et al., 2021) as well as the plantation variable (Syafi'i, 2016; Kamim, 2018). Negative values for the agricultural and plantation variables indicate a decline in the agricultural and plantation areas in certain years. Agricultural fields and plantations may be converted to other land uses, such as settlements (Kurowska et al., 2020) or mining areas (Siburian, 2015). Furthermore, mining activities surrounding agricultural and plantation areas can lead to soil degradation and reduced crop yields, causing a shift in agricultural areas away from the mining areas (Liu et al., 2021; Glina et al., 2022). The estimation model also incorporates another control variable related to land use, specifically, the size of residential areas. The estimation results for the residential area variable demonstrate a positive coefficient with $R^2 = 0.12$, coefficient value = 0.54, and p-value > 0.05. This can be explained by the relatively stable nature of residential areas over time, which indicates minimal changes in their extent.

In a broad sense, economic growth hinges on the supply and demand dynamics of critical commodities. However, the economic progress in developing nations relies heavily on technology, which entails substantial energy consumption. Sectors such as transportation, infrastructure, and industry are particularly reliant on significant energy consumption derived from nonrenewable resources to meet market demands. The utilization of coal as an energy source extends beyond domestic use, as it is also exported to other countries. Despite commitments from certain nations to reduce coal consumption and transition towards green energy, achieving this objective soon remains a formidable challenge (Bauknecht et al., 2020; Irshaid et al., 2021; Hofbauer et al., 2022; López González & Garcia Rendon, 2022; Stringer & Joanis, 2022). Meanwhile, escalating demand continues to drive increased coal procurement activities annually. This surge in coal exploitation surpasses reclamation efforts on post-mining lands, resulting in additional concerns such as devegetation and deforestation.

Conclusion

Since the enactment of the Ministry of Energy and Mineral Resources Regulation Number 43 of 2015, the issued mining business permits have declined from 10,092 in 2015 to 3,161 in 2019. Furthermore, the regression estimation results between the independent variable, the coal mining area, and the dependent variable, representing changes in forest areas, using data from 2010 to 2019, indicate a coefficient value of 0.0587 with a negative correlation. Although these estimation results are not statistically significant, it can be stated that within the 2010–2019 timeframe, any increase in the number of coal mining business permits corresponds to a decrease in the variable representing the extent of forest areas. Additionally, the regression estimation results for other independent variables, such as mineral mining, settlement areas, plantation areas, and agricultural areas, also showed a negative correlation. This implies that an increase in each of these independent variables is statistically associated with a decrease in forest area. Based on these regression estimation results, it is recommended that measures to reduce deforestation should not solely rely on policy implementation in the mining sector, but should also involve the implementation and monitoring of similar policies in agriculture and plantations. The empirical estimation results show that coal mining permits have a negative coefficient of 0.0587, which is statistically insignificant. Nevertheless, this still means that coal mining areas have eroded forest areas. However, the coefficient of the value of other mining areas has a negative value in all models and is statistically significant. However, this is partly because the areas of other mineral mining are greater than those of coal mining. Hence, permits for other mineral mining areas are distributed more evenly than those for coal mining areas.

References

Abman, R., & Carney, C. (2020a). Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in Malawi. *Journal of Environmental Economics and Management*, *103*, 102342. https://doi.org/10.1016/j.jeem.2020.102342

Abman, R., & Carney, C. (2020b). Land rights, agricultural productivity, and deforestation. *Food Policy*, *94*, 101841. https://doi.org/10.1016/j.foodpol.2020.101841

Adiatma, J. C., Arinaldo, D., & Tampubolong, A. P. (2018). *Coal dynamics and energy transition in Indonesia: The future of coal in Indonesia study*. Jakarta: Institute for Essential Services Reform (IESR).

Akram, R., Chen, F., Khalid, F., Huang, G., & Irfan, M. (2021). Heterogeneous effects of energy efficiency and renewable energy on economic growth of BRICS countries: A fixed effect panel quantile regression analysis. *Energy*, *215*, 119019. https://doi.org/10.1016/j.energy.2020.119019

Banerjee, S., Misra, A., Sar, A., Pal, S., Chaudhury, S., & Dam, B. (2020). Poor nutrient availability in opencast coalmine influences microbial community composition and diversity in exposed and underground soil profiles. *Applied Soil Ecology*, *152*, 103544. https://doi.org/10.1016/j.apsoil.2020.103544

Bauknecht, D., Andersen, A. D., & Dunne, K. T. (2020). Challenges for electricity network governance in whole system change: Insights from energy transition in Norway. *Environmental Innovation and Societal Transitions*, *37*, 318–331. https://doi.org/10.1016/j.eist.2020.09.004

Bjornlund, L. (2010). *Deforestation*. ReferencePoint Press, Inc.

Bohn, H., & Deacon, R. T. (1997). Ownership risk, investment, and the use of natural resources. *The American Economic Review*, *90*(3),526–549.

[BP] British Petroleum. (2020). *Statistical review of world energy 2020*. Retrieved from https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2020-full-report.pdf

Castro-Nunez, A., Charry, A., Castro-Llanos, F., Sylvester, J., & Bax, V. (2020). Reducing deforestation through value chain interventions in countries emerging from conflict: The case of the Colombian cocoa sector. *Applied Geography*, *123*, 102280. https://doi.org/10.1016/j.apgeog.2020.102280

Chen, J., Nan, J., Xu, D., Mo, L., Zheng, Y., Chao, L., Qu, H., Guo, Y., Li, F., & Bao, Y. (2020). Response differences between soil fungal and bacterial communities under opencast coal mining disturbance conditions. *Catena*, *194*, 104779. https://doi.org/10.1016/j.catena.2020.104779

Chong, H. T., & Collie, A. (2022). The Characteristics of Accepted Work-related Injuries and Diseases Claims in the Australian Coal Mining Industry. *Safety and Health at Work*, *13*(2), 135–140. https://doi.org/10.1016/j.shaw.2021.12.701

[DEN] Dewan Energi Nasional. (2019). *Indonesia energy outlook 2019*. Jakarta: Dewan Energi Nasional. Retrieved from https://www.esdm.go.id/assets/media/content/content-outlook-energi-indonesia-2019-bahasa-indonesia.pdf

[ESDM] Kementerian Energi dan Sumberdaya Mineral. (2019). *Statistik ketenagalistrikan tahun 2019*. Jakarta: Direktorat Jenderal Ketenagalistrikan Kementerian Energi dan Sumberdaya Mineral. Retrieved from https://gatrik.esdm.go.id/assets/uploads/download_index/files/c4053-statistik-2019-highres.pdf

[ESDM] Kementerian Energi dan Sumberdaya Mineral. (2021). *Laporan kinerja Kementerian ESDM*. Jakarta: Kementerian Energi dan Sumberdaya Mineral. Retrieved from https://www.esdm.go.id/assets/media/content/content-laporan-kinerja-kementerian-esdm-2021.pdf

[FAO] Food and Agriculture Organization. (2020). *The state of the world's forests 2020. Forests, biodiversity and people*. Rome: FAO and UNEP. Retrieved from https://doi.org/10.4060/ca8642en

Feng, S., He, W., & Li, F. (2020). Model detection and estimation for varying coefficient panel data models with fixed effects. *Computational Statistics and Data Analysis*, *152*, 107054. https://doi.org/10.1016/j.csda.2020.107054

Franco-Solís, A., & Montanía, C. V. (2021). Dynamics of deforestation worldwide: A structural decomposition analysis of agricultural land use in South America. *Land Use Policy*, *109*, 105619. https://doi.org/10.1016/j.landusepol.2021.105619

Fünfgeld, A. (2020). Coal vs climate - Indonesia's energy policy contradicts its climate goals. *German Institute of Global and Area Studies* (*GIGA*). http://www.jstor.org/stable/resrep24811

Gao, Y., Wang, J., Zhang, M., & Li, S. (2021). Measurement and prediction of land use conflict in an opencast mining area. *Resources Policy*, *71*, 101999. https://doi.org/10.1016/j.resourpol.2021.101999

Ginoga, K. L., Lugina, M., & Djaenudin, D. (2005). Kajian kebijakan pengelolaan hutan lindung. *Jurnal Penelitian Sosial dan Ekonomi*, *2*(2), 203–231. https://doi.org/10.20886/jpsek.2005.2.2.169-194

Glina, B., Mendyk, Ł., Piernik, A., Nowak, M., Maier, A., Inselsbacher, E., & Glatzel, S. (2022). Local weather conditions determine DOC production and losses from agricultural fen soils affected by open-pit lignite mining. *Catena*, *211*, 106012. https://doi.org/10.1016/j.catena.2021.106012

Gu, X., Wang, J., & Liu, Y. (2010). Water resistant features of high-risk outburst coal seams and standard discriminant model of mining under water-pressure. *Mining Science and Technology*, *20*(6), 797–802. https://doi.org/10.1016/S1674-5264(09)60284-2

Guadalupe, V., Sotta, E. D., Santos, V. F., Gonçalves Aguiar, L. J., Vieira, M., de Oliveira, C. P., & Nascimento Siqueira, J. V. (2018). REDD+ implementation in a high forest low deforestation area: Constraints on monitoring forest carbon emissions. *Land Use Policy*, *76*, 414–421. https://doi.org/10.1016/j.landusepol.2018.02.015

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill.

Hofbauer, L., McDowall, W., & Pye, S. (2022). Challenges and opportunities for energy system modelling to foster multi-level governance of energy transitions. *Renewable and Sustainable Energy Reviews*, *161*, 112330. https://doi.org/10.1016/j.rser.2022.112330

Huang, B., Lee, T. H., & Ullah, A. (2019). A combined random effect and fixed effect forecast for panel data models. *Journal of Management Science and Engineering*, *4*(1), 28–44. https://doi.org/10.1016/j.jmse.2019.03.004

[IEA] International Energy Agency. (2018). *Global energy & CO_2 status report: The latest trends in energy and emissions in 2018*. International Energy Agency. Retrieved from https://iea.blob.core.windows.net/assets/23f9eb39-7493-4722-aced-61433cbffe10/Global_Energy_and_ CO2_Status_Report_2018.pdf

Irshaid, J., Mochizuki, J., & Schinko, T. (2021). Challenges to local innovation and implementation of low-carbon energy-transition measures: A tale of two Austrian regions. *Energy Policy*, *156*, 112432. https://doi.org/10.1016/j.enpol.2021.112432

Ji, A. B., Zhang, J. J., He, X., & Zhang, Y. H. (2022). Fixed effects panel interval-valued data models and applications. *Knowledge-Based Systems*, *237*, 107798. https://doi.org/10.1016/j.knosys.2021.107798

Jiang, C., Zhao, D., Chen, X., Zheng, L., Li, C., & Ren, M. (2022). Distribution, source and ecological risk assessment of polycyclic aromatic hydrocarbons in groundwater in a coal mining area, China. *Ecological Indicators*, *136*, 108683 https://doi.org/10.1016/j.ecolind.2022.108683

Kamim, A. B. M. (2018). Perebutan ruang kehidupan dan gangguan terhadap animal rights: Studi atas konflik satwa-manusia sebagai implikasi dari ekspansi perkebunan sawit di Indonesia. *BALAIRUNG: Jurnal Multidisipliner Mahasiswa Indonesia*, *1*(2), 199–217. https://doi.org/10.22146/balairung.v1i2.42056

Kartikasari, R., Rachmansyah, A., & Leksono, A. S. (2018). The impact of coal mining on deforestation rates in Kutai Kartanegara Regency of East Kalimantan Province. *Indonesian Green Technology Journal*, *7*(1), 14–19. https://doi.org/10.21776/ub.igtj.2018.007.01.03

Kassouri, Y., Altıntaş, H., Alancioğlu, E., & Kacou, K. Y. T. (2021). New insights on the debt-growth nexus: A combination of the interactive fixed effects and panel threshold approach. *International Economics*, *168*, 40–55. https://doi.org/10.1016/j.inteco.2021.08.001

Kazungu, M., Ferrer Velasco, R., Zhunusova, E., Lippe, M., Kabwe, G., Gumbo, D. J., & Günter, S. (2021). Effects of household-level attributes and agricultural land-use on deforestation patterns along a forest transition gradient in the Miombo landscapes, Zambia. *Ecological Economics*, *186*, 107070. https://doi.org/10.1016/j.ecolecon.2021.107070

[KLHK] Kementerian Lingkungan Hidup dan Kehutanan. (2021). *Laporan inventarisasi gas rumah kaca (GRK), dan monitoring, pelaporan, verifikasi (MPV)*. Jakarta: Kementerian Lingkungan Hidup dan Kehutanan.

Konicek, P., & Waclawik, P. (2018). Stress changes and seismicity monitoring of hard coal longwall mining in high rockburst risk areas. *Tunnelling and Underground Space Technology*, *81*, 237–251. https://doi.org/10.1016/j.tust.2018.07.019

[KPK] Komisi Pemberantasan Korupsi. (2018). *Nota sintesis - Evaluasi gerakan nasional penyelamatan sumber daya alam 2018*. Jakarta: Komisi Pemberantasan Korupsi.

Kurowska, K., Kryszk, H., Marks-Bielska, R., Mika, M., & Leń, P. (2020). Conversion of agricultural and forest land to other purposes in the context of land protection: Evidence from Polish experience. *Land Use Policy*, *95*, 104614. https://doi.org/10.1016/j.landusepol.2020.104614

Laing, T. (2019). Small man goes where the large fears to tread: Mining in Guyana: 19902018. *Resources Policy*, *63*, 101426. https://doi.org/10.1016/j.resourpol.2019.101426

Landry, J. S., & Matthews, H. D. (2016). Non-deforestation fire vs. fossil fuel combustion: The source of CO_2 emissions affects the global carbon cycle and climate responses. *Biogeosciences*, *13*(7), 2137–2149. https://doi.org/10.5194/bg-13-2137-2016

Lee, Y., Mukherjee, D., & Ullah, A. (2019). Nonparametric estimation of the marginal effect in fixed-effect panel data models. *Journal of Multivariate Analysis*, *171*, 53–67. https://doi.org/10.1016/j.jmva.2018.11.013

Li, G., Hu, Z., Li, P., Yuan, D., Wang, W., & Yang, K. (2021). The optimal framework and model to balance underground coal mining and cropland protection in Jining, eastern China. *Resources Policy*, *74*, 102307. https://doi.org/10.1016/j.resourpol.2021.102307

Li, G., Hu, Z., Li, P., Yuan, D., Wang, W., Han, J., & Yang, K. (2022). Optimal layout of underground coal mining with ground development or protection: A case study of Jining, China. *Resources Policy*, *76*, 102639. https://doi.org/10.1016/j.resourpol.2022.102639

Liu, X., Chen, S., Yan, X., Liang, T., Yang, X., El-Naggar, A., Liu, J., & Chen, H. (2021). Evaluation of potential ecological risks in potential toxic elements contaminated agricultural soils: Correlations between soil contamination and polymetallic mining activity. *Journal of Environmental Management*, *300*, 113679. https://doi.org/10.1016/j.jenvman.2021.113679

Long, N. V. (1975). Resource extraction under the uncertainty about possible nationalization. *Journal of*

Economic Theory, *10*(1), 42–53. https://doi.org/10.1016/0022-0531(75)90060-5

López González, D. M., & Garcia Rendon, J. (2022). Opportunities and challenges of mainstreaming distributed energy resources towards the transition to more efficient and resilient energy markets. *Renewable and Sustainable Energy Reviews*, *157*, 112018. https://doi.org/10.1016/j.rser.2021.112018

Lu, X., & White, H. (2014). Robustness checks and robustness tests in applied economics. *Journal of Econometrics*, *178*, 194–206. https://doi.org/10.1016/j.jeconom.2013.08.016

Ma, Q., Wu, J., He, C., & Fang, X. (2021). The speed, scale, and environmental and economic impacts of surface coal mining in the Mongolian Plateau. *Resources, Conservation and Recycling*, *173*, 105730. https://doi.org/10.1016/j.resconrec.2021.105730

Mueller, R. M. (2022). Surface coal mining and public health disparities: Evidence from Appalachia. *Resources Policy*, *76*, 102567. https://doi.org/10.1016/j.resourpol.2022.102567

Mullan, K., Caviglia-Harris, J. L., & Sills, E. O. (2021). Sustainability of agricultural production following deforestation in the tropics: Evidence on the value of newly-deforested, long-deforested and forested land in the Brazilian Amazon. *Land Use Policy*, *108*, 105660. https://doi.org/10.1016/j.landusepol.2021.105660

Müller-Hansen, F., Heitzig, J., Donges, J. F., Cardoso, M. F., Dalla-Nora, E. L., Andrade, P., Kurths, J., & Thonicke, K. (2019). Can intensification of cattle ranching reduce deforestation in the Amazon? Insights from an agent-based social-ecological model. *Ecological Economics*, *159*, 198–211. https://doi.org/10.1016/j.ecolecon.2018.12.025

Nazir, N., & Ahmad, S. (2018). Forest land conversion dynamics: A case of Pakistan. *Environment, Development, and Sustainability*, *20*, 389–405. https://doi.org/10.1007/s10668-016-9887-3

Ngoma, H., Pelletier, J., Mulenga, B. P., & Subakanya, M. (2021). Climate-smart agriculture, cropland expansion and deforestation in Zambia: Linkages, processes and drivers. *Land Use Policy*, *107*, 105482. https://doi.org/10.1016/j.landusepol.2021.105482

Norberg, J. (1999). Linking nature's services to ecosystems: Some general ecological concepts. *Ecological Economics*, *29*(2), 183202. https://doi.org/10.1016/S0921-8009(99)00011-7

Peng, B., Yu, J., & Zhu, Y. (2021). A heteroskedasticity robust test for cross-sectional correlation in a fixed effects panel data model. *Economics Letters*, *201*, 109799. https://doi.org/10.1016/j.econlet.2021.109799

[PLN] Perusahaan Listrik Negara. (2020). *Statistik PLN 2019*. Jakarta: Perusahaan Listrik Negara. Retrieved from https://web.pln.co.id/statics/uploads/2020/08/Statistik-2019-4-8-20-rev.pdf

Rahman, M. F., & Islam, K. (2021). Effectiveness of protected areas in reducing deforestation and forest fragmentation in Bangladesh. *Journal of Environmental Management*, *280*, 111711. https://doi.org/10.1016/j.jenvman.2020.111711

Rodríguez-de-Francisco, J. C., del Cairo, C., Ortiz-Gallego, D., Velez-Triana, J. S., Vergara-Gutiérrez, T., & Hein, J. (2021). Post-conflict transition and REDD+ in Colombia: Challenges to reducing deforestation in the Amazon. *Forest Policy and Economics*, *127*, 102450. https://doi.org/10.1016/j.forpol.2021.102450

Saputra, B., & Mahmudi. (2012). Pengaruh desentralisasi fiskal terhadap pertumbuhan ekonomi dan kesejahteraan masyarakat. *Jurnal Akuntansi dan Auditing Indonesia*, *16*, 185–199.

Siburian, R. (2015). Antara pertanian dan pertambangan batubara: Studi perebutan lahan di Kecamatan Tenggarong Seberang. *Jurnal Masyarakat & Budaya*, *17*, 233–248. https://doi.org/10.14203/jmb.v16i1.44

Siqueira-Gay, J., Sonter, L. J., & Sánchez, L. E. (2020). Exploring potential impacts of mining on forest loss and fragmentation within a biodiverse region of Brazil's northeastern Amazon. *Resources Policy*, *67*, 101662. https://doi.org/10.1016/j.resourpol.2020.101662

Solechah, S. N. (2012). Realisasi desentralisasi sektor pertambangan. *Jurnal Info Singkat Pemerintahan Dalam Negeri*, *4*, 17–20.

Stringer, T., & Joanis, M. (2022). Assessing energy transition costs: Sub-national challenges in Canada. *Energy Policy*, *164*, 112879. https://doi.org/10.1016/j.enpol.2022.112879

Sunderlin, W. D., & Resosudarmo, I. A. P. (1997). *Laju dan penyebab deforestasi di Indonesia: Penelaahan kerancuan dan penyelesaiannya* (Occasional Paper No. 9). Bogor: CIFOR.

Supriatna, J., Shekelle, M., Fuad, H. A. H., Winarni, N. L., Dwiyahreni, A. A., Farid, M., Mariati, S., Margules, C., Prakoso, B., & Zakaria, Z. (2020). Deforestation on the Indonesian island of Sulawesi and the loss of primate habitat. *Global Ecology and Conservation*, *24*, e01205. https://doi.org/10.1016/j.gecco.2020.e01205

Syafi'i, I. (2016). Konflik agraria di Indonesia: Catatan reflektif konflik perkebunan Sawit di Kalimantan Timur. *Jurnal Masyarakat & Budaya*, *18*, 415–432. https://doi.org/10.14203/jmb.v18i3.572

Trigg, A. B., & Richard Dubourg, W. (1993). Valuing the environmental impacts of opencast coal mining in the

UK: The case of the Trent Valley in North Staffordshire. *Energy Policy*, *21*(11), 1110–1122. https://doi.org/10.1016/0301-4215(93)90261-D

Villén-Pérez, S., Anaya-Valenzuela, L., Conrado da Cruz, D., & Fearnside, P. M. (2022). Mining threatens isolated indigenous peoples in the Brazilian Amazon. *Global Environmental Change*, *72*, 102398. https://doi.org/10.1016/j.gloenvcha.2021.102398

Vuola, M. (2022). The intersections of mining and neoliberal conservation. *World Development*, *1502*, 105816. https://doi.org/10.1016/j.worlddev.2022. 105816

Wahyuni, H., & Suranto, S. (2021). Dampak deforestasi hutan skala besar terhadap pemanasan global di Indonesia. *JIIP: Jurnal Ilmiah Ilmu Pemerintahan*, *6*(1), 148–162. https://doi.org/10.14710/jiip.v6i1.10083

Wang, Y. Q., Wang, Z. F., & Cheng, W. C. (2019). A review on land subsidence caused by groundwater withdrawal in Xi'an, China. *Bulletin of Engineering Geology and the Environment*, *78*(4), 2851–2863. https://doi.org/10.1007/s10064-018-1278-6

Yang, D., Qiu, H., Ma, S., Liu, Z., Du, C., Zhu, Y., & Cao, M. (2022). Slow surface subsidence and its impact on shallow loess landslides in a coal mining area. *Catena*, *209*, 105830. https://doi.org/10.1016/j.catena.2021.105830

Zaman, K. (2022). Environmental cost of deforestation in Brazil's Amazon rainforest: Controlling biocapacity deficit and renewable wastes for conserving forest resources. *Forest Ecology and Management*, *504*, 119854. https://doi.org/10.1016/j.foreco.2021.119854

Zhang, P., Ye, Q., & Yu, Y. (2021). Research on farmers' satisfaction with ecological restoration performance in coal mining areas based on fuzzy comprehensive evaluation. *Global Ecology and Conservation*, *32*, e01934. https://doi.org/10.1016/j.gecco.2021.e01934