The Forest Be Mine: Analyzing the Impact of Mines on Deforestation in Indonesia

Bachelor Thesis

Max Heinze (h11742049@wu.ac.at)

supervised by Jesús Crespo Cuaresma and Nikolas Kuschnig

Vienna University of Economics and Business

Department of Economics

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Abstract

Deforestation is a known environmental problem worldwide and particularly pronounced in Indonesia. Mining is an important contributor to the Indonesian economy and has been shown to be a driver of deforestation in other settings. In this thesis, I investigate the link between mining activity in Indonesia and forest cover loss in the affected regions. Using a two-way fixed effects panel model, I find that an increase in mining activity has a significant negative effect on forest cover, both its area and the share of a municipality's territory it occupies. Political and public scrutiny of unsustainable mining practices will therefore be necessary to allow Indonesia to adhere to its own forest conservation pledges.

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1 Introduction

Globally, tree cover is declining. According to data from the Food and Agriculture Association of the United Nations (FAO, 2021), global forest cover declined from 41.1 million km^2 in 2010 to 40.6 million km^2 in 2020, an average annual decline of 0.12 percent. This development is most pronounced in Africa, Central America and South Asia. In Indonesia, which will be the focus of this work, forest loss is particularly severe: Indonesian tree cover decreased by an annual average of 0.78 percent in the past decade. Combined with the large extent of Indonesian forests, this implies that Indonesia accounts for the third-largest loss in net forest cover since 2010, after Brazil and the Democratic Republic of the Congo. While tropical forests fulfill a number of central economic functions for these countries, their importance for the environment is equally high. When forest is lost, this imbalance can have detrimental effects on biodiversity, the climate, economic activity, public health, and other facets of our and other species' well-being. Among other issues, forest loss is associated with more extreme local temperature changes, decreased food security, increased risk of extinction for large numbers of species, and deterioration of public health due to increased transmission of diseases like Malaria (Garg, 2019; Giam, 2017; Vargas Zeppetello et al., 2020).

The drivers of deforestation are diverse, and have been well-studied both with regard to forests globally (see Busch & Ferretti-Gallon, 2017, for a meta-analysis) and within Indonesia (see e.g. Austin et al., 2019; Wijaya et al., 2015). Mining activity has been found to be a consistent, albeit minor driver of deforestation, even though the bulk of forest loss can be attributed to agriculture. Exploitation of Indonesia's vast natural resources contributes sizably to the nation's economy: In 2020, mining and quarrying activity accounted for IDR 994 trillion of the total GDP of IDR 15.4 quadrillion. Measured at constant 2010 prices, the mining product had increased by an average 0.96 percent annually since 2010. However, in the same period, the share of the nation's GDP attributed to mining decreased from 10.46 percent to 7.36 percent, as other sectors, especially in retail and service industries, experienced more growth (Badan Pusat Statistik [BPS], 2022). Despite this, exploitation of Indonesia's natural resources remains an important part of the country's economy. The question whether and how this can be reconciled with natural preservation efforts will continue to be discussed politically both in Indonesia and internationally, and information on the causes and drivers of deforestation is vital for policy-makers to be able to abate the negative consequences of forest cover loss.

In this bachelor thesis, I will therefore analyze the impact that mining activity has had on tree cover loss in Indonesia during the past decade. For this, I will create an index that quantifies mining activity over time for each of the country's municipalities, called cities and regencies. I will then construct a panel including the mining activity index, tree cover data and variables on socioeconomic development, which allows to estimate the effect of mining on deforestation accounting for city/regency and year fixed effects.

2 Literature Review

With 49 percent of the country covered by forest, Indonesia has the world's eight-largest forest area, and the third-largest among countries with tropical climate (FAO, 2021). The soil of Indonesian forests' peatlands, a swampy type of tropical ecosystem especially prominent in Indonesia's and neighboring countries' forests, has been found to be home to a considerable number of endangered species (Posa et al., 2011) and store large amounts of carbon in addition to the carbon stored by vegetation itself (Warren et al., 2017). When this land is converted, this carbon is released into the atmosphere, exacerbating the negative climate effect from plain biomass loss. In total, Indonesian forests are estimated to store between 10 and 25 Gt of carbon (Gibbs et al., 2007), which corresponds to 1.03–2.56 times annual global carbon emissions in 2021 (International Energy Agency [IEA], 2022).

Ranking third in deforestation since 2010 (FAO, 2021), Indonesia shares some characteristics with other forest-losing countries and differs in others. Large-scale conversion of Indonesian forests started before the 1980s, when rural population increased and farmers commenced agricultural activities in previously uncultivated areas. By the late 1990s, influence of small-scale farming had given way to much larger and more impactful oil palm plantations (Rudel et al., 2009). The rate of Indonesian forest loss has since continued to increase, whereas it began to decrease in Brazil, which had started implementing effective forest conservation policies in the early 2000s (Assunção et al., 2015; FAO, 2021). By 2012, Indonesia had also surpassed Brazil in loss of primary forest, which stores higher amounts of carbon and is home to more species than other types of tree cover (Margono et al., 2014). While Indonesian deforestation has also changed recently, it has not slowed: The share of forest lost to large-scale oil palm plantations has begun to decrease, but other drivers, like timber plantations and conversion to shrubland (often an effect of fire activity) have gained in importance. The effect of mining also appeared to increase, albeit at lower levels (Austin et al., 2019).

The issue of forest conservation is politically recognized to be a problem in Indonesia, although the government's response has not always been consistent and continues to be plagued by conflicting goals of sustainable forest management and further economic development. The first law acknowledging the importance of forest management was passed in 1967 (The President of the Republic of Indonesia, 1967), and in 1971, the Directorate General for Forestry, a government agency concerned with forest management, was formed. Today, forest management is the responsibility of the Ministry of Environment and Forestry (Ministry of Environment and Forestry of the Republic of Indonesia [MENLHK], n.d.). Although Indonesia has signed a pledge to end all deforestation by 2030 at the COP26 climate summit in Glasgow in 2021, unclear statements by government officials have led news media to question the country's commitment to that goal (Ungku & Widianto, 2021).

In past decades, researchers from multiple disciplines have analyzed which factors effect a decrease in natural forest cover. Busch and Ferretti-Gallon (2017) provide a meta-analysis of 121 studies on this subject. They find that rates of deforestation are consistently found to be influenced by agricultural activity, built infrastructure, the legal environment and broader socioeconomic characteristics.

In tropical regions, agricultural activity accounts for the greatest share of forest loss (Hosonuma et al., 2012). The pronounced negative environmental effects of oil palm plantations, which often require removal of large pieces of tropical forest, have been studied for multiple decades (Fitzherbert et al., 2008). Oil palm plantations are particularly widespread in South Asian countries such as Malaysia and Indonesia, and have been found to account for 23 percent of Indonesian forest loss (Austin et al., 2019). However, expansion of oil palm farming has begun to shift towards areas not previously covered by tropical forest, which led to this rate stabilizing despite an increase in areas dedicated to oil palm plantations (Austin et al., 2017). Production of timber accounts for 15 percent of Indonesian deforestation (Austin et al., 2019). However, its relationship to forest cover has not always been found to be negative, as consistent use of a forest for logging purposes may prevent other, more invasive uses of a given area (Busch & Ferretti-Gallon, 2017).

Built infrastructure is another factor commonly associated with deforestation that has been studied extensively (Busch & Ferretti-Gallon, 2017). Forest that is situated near urban areas, or in areas with extensive road networks, tends to be more prone to being converted for economic activities. However, the question of causality is more difficult to answer here: Roads and other infrastructure may be built in proximity to plantations, logging sites, and mines for the purpose of transporting goods, and the associated forest loss may therefore be indirectly linked to them. Sociodemographic and human development variables have also been used to explain forest loss. Low-income regions tend to have lower rates of forest loss (Busch & Ferretti-Gallon, 2017). Even though some of the studies surveyed by Busch and Ferretti-Gallon (2017) find that high incomes were also associated with less deforestation, evidence pointing to whether there exists an Environmental Kuznets Curve for deforestation was generally inconclusive (Choumert et al., 2013). Other factors like more focused law enforcement, which is associated with less illegal conversion of forests to plantations (Tacconi et al., 2019), may explain differences between deforestation rates in different countries, but are difficult to quantify on a subnational level.

While deforestation linked to large plantations has started to stagnate, or at least be counteracted politically (Busch et al., 2015), mining has only more recently been focused on as a driver of forest loss. Austin et al. (2019) report mining to be a comparatively minor factor in driving loss of primary forest, at 2 percent, but with an increasing trend. Similarly, Abood et al. (2015) find that 2.1 percent of Indonesian forest loss between 2000 and 2010 occurred on land zoned for mining use. However, the impact of mining activity on tropical forests goes beyond plain conversion of forest-covered land into mines, as roads, administrative buildings and even worker accommodations frequently have to be built in their surroundings. In Brazil, mining has accounted for 9 percent of Amazon rainforest loss between 2005 and 2015, with indirect forest loss outside mines' premises exceeding direct deforestation twelvefold (Sonter et al., 2017). It is to be expected that mining-induced forest loss in Indonesia entails a similar indirect component.

Based on the literature reviewed above, I hypothesize that the presence of a mine negatively influences forest cover in its surroundings. In order to estimate the total effect, I will use a panel of all municipalities in Indonesia over a period of ten years featuring data on local forest cover and mining activity, controlling for socioeconomic development (see Section 3 and 4 for further detail). In order not to underestimate the indirect effect on forest cover via construction of auxiliary infrastructure, controls on road accessibility and area of urban settlements are not included.

3 Data

3.1 Extent of the Cities and Regencies

Administratively, Indonesia is divided into 34 provinces, which in turn are comprised of a total of 522 cities and regencies, a subdivision comparable to municipalities in other countries.[1] These subdivisions as well as their exact geographical extent, both

[1]Because there are no differences between cities and regencies that would be relevant for this thesis, I sometimes use the term "municipalities" to refer to both cities and regencies for reasons of legibility.

for provinces and cities/regencies, are provided as a shapefile by the Indonesian Statistics office Badan Pusat Statistik (2020), via the United Nations Office for the Coordination of Humanitarian Affairs Centre for Humanitarian Data. Figure 1 shows a map of all cities and regencies, with cities, which are less numerous and concentrated around urban settlements, colored in red.

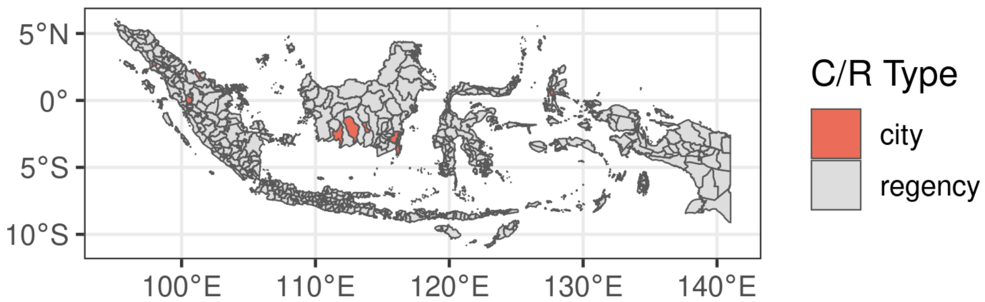

Figure 1: Map of Indonesia with borders of all cities and regencies. Cities are marked in red.

Within the scope of this thesis, I use the shapefiles to allocate data on land use and mining activity, which, as outlined below, are available in raster format, to their respective municipalities. The reason that I use cities and regencies for my analysis is that I expect them to be heterogeneous in terms of mining activity, environmental state, and socioeconomic development. At the same time, they are comparable, as mining regulation and permits are matters of the central government and there are therefore no mining-related institutional differences between individual municipalities (The President of the Republic of Indonesia, 2020).

3.2 Land Use

The European Space Agency provides annually updated, remotely sensed data on land use. For years 2010 to 2015, I used data available from version 2.0.7 of the dataset (European Space Agency [ESA], 2017), and for years 2016 to 2020, I used data from version 2.1 (ESA, 2021). This data provides land use classification for pixels measuring 300 by 300 meters. There is a total of 22 land use categories, which I aggregated to five broader categories: tree cover, cropland, other vegetation, urban settlements, and water surface. The tree cover category, which is the focus of my analysis, consists of what was originally classified as broadleaved tree cover, needleleaved tree cover, tree cover flooded with fresh water, and tree cover flooded with saline water.

Figure 2 shows the relative prevalence of forest cover on a city/regency level for the most recent year included in the data, 2020. Forest cover is especially high on the island of New Guinea, as well as some center parts of the island of Borneo and areas near the western shoreline of Sumatra. The lowest tree cover levels are generally observed in Eastern Sumatra and on the island of Java.

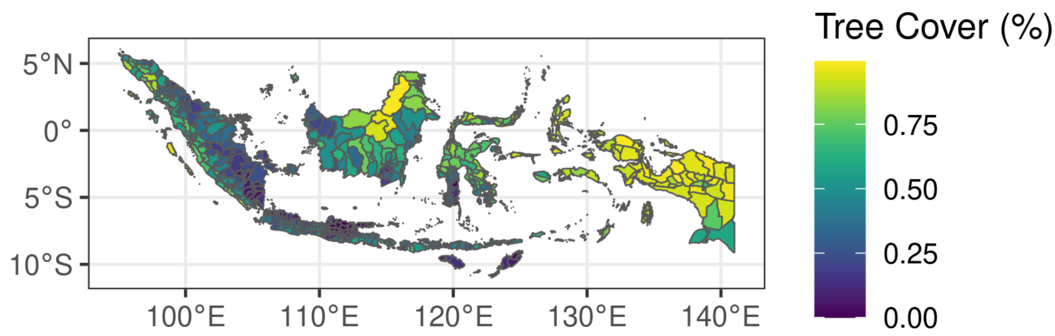

Figure 2: Amount of surface covered by trees as a percentage of the total surface of the given city or regency, 2020.

In addition to the percentage of surface covered by trees in any given municipality, I also created a measurement of total forest-covered area per city/regency by multiplying the percentage of tree cover with their respective areas.

3.3 Mining Activity

Maus et al. (2020) provide a dataset including a comprehensive account of areas worldwide, including in Indonesia, that are currently used for mining. What the dataset does not provide, however, is an account of mining activity over time. In order to be able to estimate a panel model, I therefore encounter the problem of approximating the extent of variation that there is in mining activity for each mine over time.

Elvidge et al. (2021) provide annual aggregates of light emissions at night using imagery collected by the NASA/NOAA Visible Infrared Imaging Radiometer Suite (VIIRS). The data is available in raster format at a resolution of 15 arc seconds (about 463 meters at the equator) and is stripped of stray lights and other outliers such as sunlight, moonlight or light emitted by biomass burning. I used the annually aggregated median masked values provided in the dataset for approximating mining activity.

Intersecting the geographical extent of each individual mine provided by Maus et al. (2020), widened by a buffer zone of 10 arc seconds (around 309 meters at the equator) in each direction, with the nightlight data, I obtained a collection of light points on the territory of each individual mine (including the buffer). I used the median of the light intensity values for each night light data point per buffered mining polygon as an aggregate per mine in order to decrease the influence of outliers.

However, for many mines, the measured night light activity is zero. The upper panel of Figure 3 shows the distribution of night light aggregates for all mines and years. In total, there were 8613 year-mine data points, of which 4456 had value zero. The reasons for why this outcome occurs are difficult to asses and could range from operation being limited to daytime to actual abandonment of the site. In absence of a method to identify abandoned mines and remove them, I decided to adjust the measured night light emission figures, differentiating between mines that had not emitted light in any of the years covered, and mines that had emitted light in at least one of the years.

I therefore split the dataset into two parts. The zero values of the mines in the part consisting of mines never emitting any light during the observation period were then substituted by the median night light activity of all other mines in the given year. This way, zero night light values for mines that had emitted light in some other

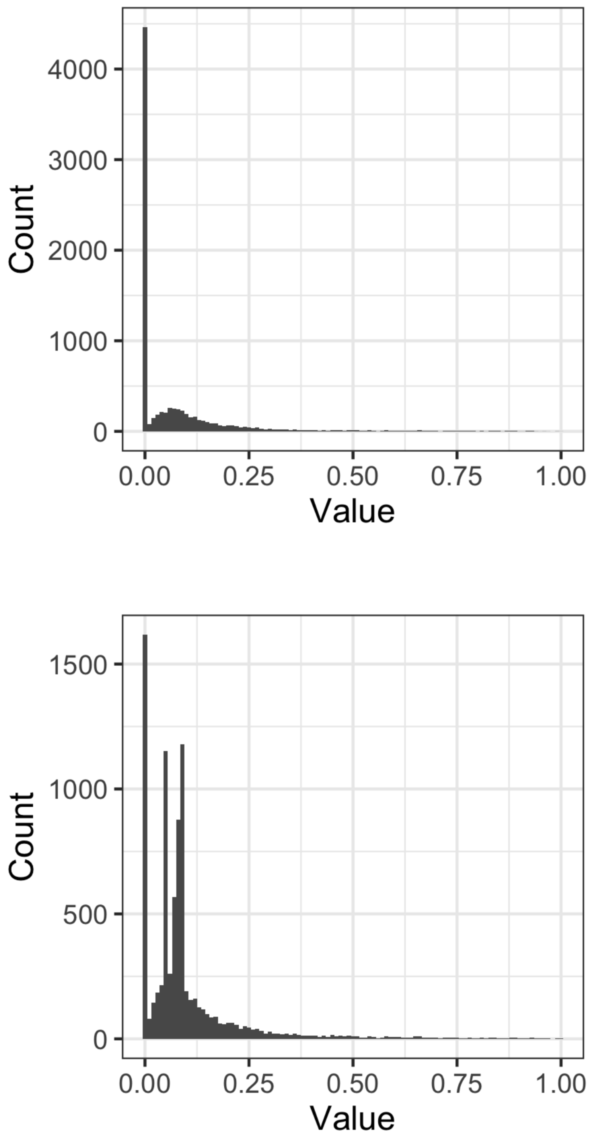

Figure 3: Distribution of year-mine night light aggregates before any adjustments made (upper panel) and after replacing zero values for mines that had them across all years (lower panel). The x-axis is cut off at 1 for reasons of clarity, as there exists a small number of mines with night light values well above 1.

year were preserved, for they could indicate actual inauguration or abandonment of a mine. The lower panel of Figure 3 shows the number of zeroes greatly reduced, with the overall distribution similar to the way it was before.

As the polygons provided by Maus et al. (2020) represent the plain *area* of a mine, and aggregated night light values are a (proxy) measure of mining intensity *per area* (as those were aggregated as medians of a number of raster data points), I constructed the following mining activity index to proceed:

$$activity_{mt} = area_m \cdot light_{mt}, \tag{1}$$

where *activity* is the mining activity index, *area* is the mining area from Maus et al. (2020), *light* is the adjusted median night light value, and m, t are indices for individual mines and years, respectively.

As this index is the product of an area measurement and an approximate measurement of mining activity per area, the resulting index is, conceptually, a measurement of mining activity. The index can therefore be treated as an absolute measurement; a mine with a mining activity of $2x$ should therefore (hypothetically) exert the same pressure on forests in its environment as two mines with a mining activity of x.

Compared to approximating the development of mining activity over time, aggregating the indices to the city/regency level was quite straightforward. I uniquely assigned each mine to a city or regency, depending on which of these entities the centroid of the mining area was located in. This leads to trivial mining activity indices for municipalities with either one mine or no mine at all (i.e., the index of the mine or zero, respectively). For cities or regencies with multiple mines on their territory, I created an aggregate mining index by summing up indices of all individual mines within their borders. This is possible due to the absolute measurement character of the index, which I outlined above. Aggregation of the mining index to city/regency level can therefore be summarized as follows:

$$activity_{it} = \begin{cases} 0 & \text{if } M = 0 \\ \sum_{m=1}^{M} activity_{mt} & \text{if } M > 0 \end{cases}, \tag{2}$$

where M is the number of mines in a city or regency and i is an index for the individual cities and regencies.

Figure 4, which displays cities and regencies that contain at least one operational mine in 2020, the latest year considered, shows that mining activity is largely concentrated in Kalimantan, on the island of Borneo; as well as a number of regencies in Sumatra inland; and some isolated places on the other islands. From Figure 5, which shows the mining activity index for all municipalities in 2020, it can additionally be seen that mining is most intensive in Eastern Kalimantan, especially in the regencies of Kutai Kartanegara and Kutai Timur, which show up in bright green and yellow on the map (I will discuss this in more detail in Section 4). Some other regencies on the island of Borneo also show elevated levels of mining activity, as compared to the majority of other mine-containing municipalities, including all that lie on different islands.

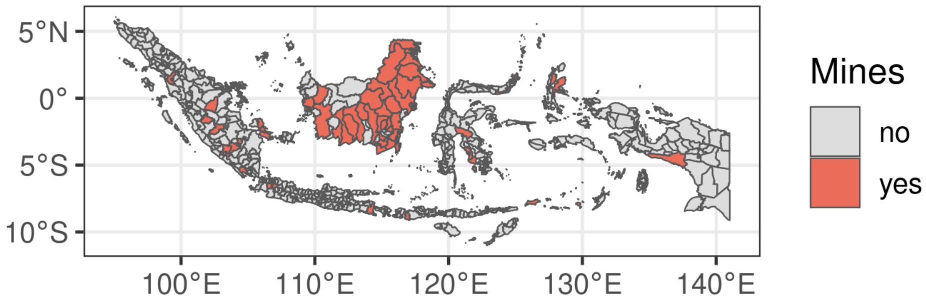

Figure 4: Presence of mines (as determined by the mining activity index being greater than zero) in 2020.

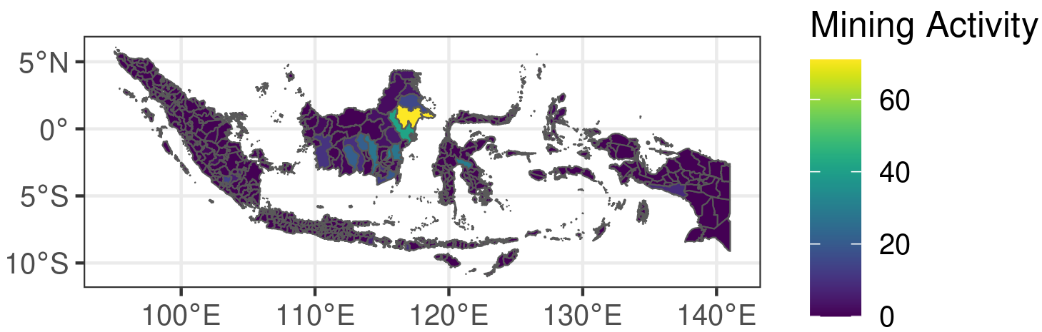

Figure 5: Mining activity, as measured by the mining activity index, in 2020.

3.4 Socioeconomic Data

Socioeconomic data on city/regency level, which I use to control for general socioeconomic development and its effect on environmental degradation, is available from the Indonesian Statistics Office. They provide data on the Human Development Index (HDI) for each city and regency (BPS, 2021c), as well as the index's components, average monthly expenditure (BPS, 2021a), life expectancy at birth (BPS, 2021e), mean years of schooling (BPS, 2021d) and expected years of schooling (BPS, 2021b).

Figure 6 shows the Human Development Index by city/regency in 2020. The highest levels of socioeconomic development as measured by the HDI are generally observed in urban areas in and around large cities, such as the capital Jakarta in Western Java. In contrast, rural areas in Western New Guinea are the least developed. In rural areas on all other islands, HDI values are largely homogeneous, with slightly higher levels occurring in the surroundings of urban agglomerations and Eastern Kalimantan.

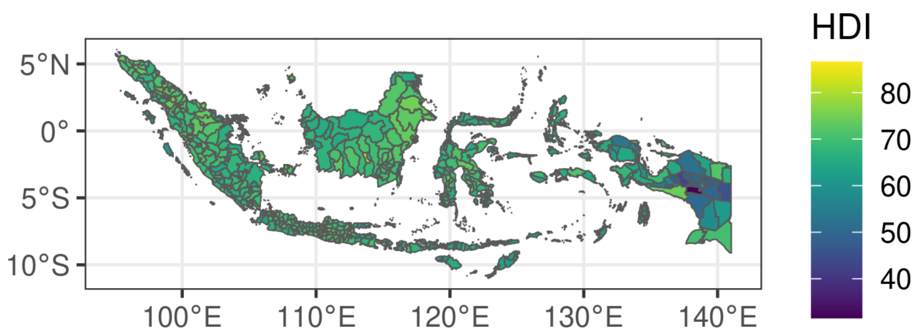

Figure 6: HDI by city/regency in 2020.

The individual components of the HDI, which are also reported by the Indonesian Statistics Office, largely share a similar regional distribution, which leads to pronounced positive correlations between the individual variables, as seen in Figure 7. An exception is life expectancy at birth, which is more evenly distributed across Indonesia, meaning that Indonesians in urban areas tend to only live a little longer than rural Indonesians, which contrasts with the stark differences in expenditure and schooling.

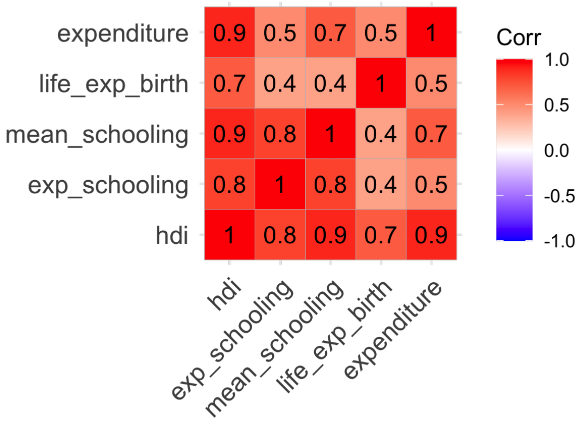

Figure 7: Correlations between different components of the HDI and the HDI itself, across all cities/regencies and years. Red tiles indicate positive correlations.

4 Methods

As detailed in Section 2, I hypothesize that mining activity, as measured by the mining activity index (see Section 3), negatively influences tree cover area and the relative share of land covered by trees in a given city or regency. To model this econometrically, I constructed a panel of all cities and regencies ($i = 1, 2, \ldots, N$) over time ($t = 1, 2, \ldots, T$), containing both outcome variables (tree cover percentage tp_{it} and tree cover area ta_{it}), two types of explanatory variables (presence of a mine as a dummy variable $mine_{it}$ and mining activity $activity_{it}$) as well as the available socioeconomic control variables (monthly expenditure, expected schooling and life expectancy at birth)[2].

To estimate the effect of mine presence (Models 1 and 2 below) or mining activity (Models 3 to 6 below) on forest cover, I use a two-way fixed effects model with both city/regency fixed effects and year fixed effects. Using this type of model allows for

[2]From the available data, HDI and mean schooling are excluded because mean schooling correlates strongly with expected schooling and HDI is a combination of the other variables.

consistent estimation while controlling for unobservable time-specific or city/regency specific characteristics, e.g., law enforcement getting stricter over time—by the same degree in all municipalities—or a certain regency having extraordinarily attractive coal resources—regardless of the year (Wooldridge, 2010).

Model 1, with tree cover percentage as dependent variable and the mining dummy variable as explanatory, is specified as follows:

$$tp_{it} = mine_{it}\beta + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \mu_i + \psi_t + \varepsilon_{it}, \tag{3}$$

where tp_{it} is the share of a city's or regency's area that is covered by forest, md_{it} is a dummy variable that is 1 for municipalities with one or more mines and 0 otherwise, β is the coefficient associated with it, $\boldsymbol{x}'_{it}$ is a row vector containing values of all control variables for any pair of (i, t), $\boldsymbol{\gamma}$ is a column vector containing the associated coefficients, μ_i is the city/regency fixed effect, ψ_t is the year fixed effect, and ε_{it} is the error term.

Model 2 is different from Model 1 only in that it takes tree cover *area* ta_{it}, instead of share, as dependent variable:

$$ta_{it} = \beta mine_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \mu_i + \psi_t + \varepsilon_i t. \tag{4}$$

Models 3 and 4 are specified analogously to Models 1 and 2, but take the mining activity index (aggregated to city/regency level) $activity_{it}$ instead of the dummy as explanatory variable:

$$tp_{it} = \beta activity_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \mu_i + \psi_t + \varepsilon_i t \tag{5}$$

and

$$ta_{it} = \beta activity_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \mu_i + \psi_t + \varepsilon_i t, \tag{6}$$

respectively.

As seen in Section 3 and explicitly visible in Figure 5, there are a number of municipalities in Eastern Kalimantan whose mining values are exceptionally high. Even though some concentration of effects can be expected due to Kalimantan being a prominent mining area, I decided to formally investigate potential issues with outliers.

I therefore counted the number of mines from Maus et al. (2020) for each city and regency, and averaged the mining activity index over all years observed. The distributions of these two measurements can be seen in Figure 8. The lower panel shows that two regencies' mining activity index averages exceed 30: That of Kutai Timur ($\overline{activity}_i = 46.3$) and that of Kutai Kartanegara ($\overline{activity}_i = 37.7$). However, Kutai Kartanegara's exceptionally high value can be explained by the presence of a total of 252 mines on the regency's territory (an outlier well visible in the upper panel of Figure 8). Kutai Timur, however, does not have an extraordinaly high number of mines, at 33.

Since the mine-site night light data extracted from Elvidge et al. (2021) could be vulnerable to influence by other factors than mining activity, and there are no structural differences between Kutai Timur and other municipalities that would justify the average mining activity index being that much higher, I decided to estimate Models 3 and 4 again, this time excluding Katai Timur from the sample.

Models 5 and 6 are therefore specified as

$$tp_{it} = \beta activity_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \mu_i + \psi_t + \varepsilon_i t, \tag{7}$$

and

$$ta_{it} = \beta activity_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \mu_i + \psi_t + \varepsilon_i t, \tag{8}$$

again, but this time with $i = 1, 2, \ldots, (N-1)$.

5 Results and Discussion

Table 1 shows the results of Models 1 through 6.

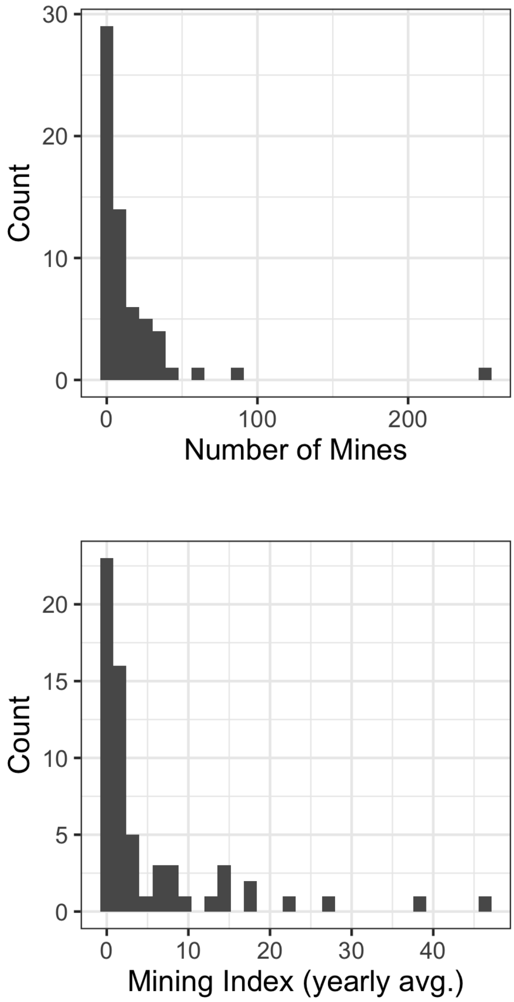

Figure 8: Upper Panel: Histogram of the number of mines found in each city/regency. Lower Panel: Histogram of mining activity values calculated for each city/regency.

In both Models 1 and 2, I find a significant negative effect of the presence of one or more mines on both the total area that is covered by trees and the tree-covered share of a city's or regency's area. In these two models, interpretation of the magnitude of the coefficient is possible and meaningful. Therefore, commencement of any mining activity in a given municipality will lead to an average decrease in forest cover by 0.06 square kilometers, or 0.9 percentage points, holding all other things constant. All control variables that were included in the model appear to have a significant positive effect on both tree cover share and area, with the exception of expected schooling, which does not have an effect on the tree cover area. In line with the reasoning of including the components of the HDI as a measure for socioeconomic development of a municipality, this can be interpreted in such way as that a more developed city or regency will, on average, elicit less deforestation. F-statistics for both models show them to be significantly better at explaining deforestation than a model with no independent variables at all.

The results of Models 3 and 4 are perhaps more interesting, as these models make use of the mining activity index that I constructed using a combination of remotely sensed mining polygons and night light data (see Section 3). In this case, however, an intuitive interpretation of the magnitude of the coefficients associated with mining activity is not possible due to the properties of the index, which does not have an intuitive interpretation either. Only the sign and significance of the coefficients can be read intuitively: In these models, no effect of mining activity on tree cover can be found, while there is a significant negative effect of an increase of mining activity on the share of a municipality that is covered by trees. Effects of the control variables are the same as in Models 1 and 2, and F-statistics show the models to be significant as a whole.

Finally, as outlined above in 4, Models 5 and 6 share the same model specification as Models 3 and 4, but the regency of Kutai Timur, whose mining activity index is higher than the amount of mines located there would suggest, is excluded from the sample. Here, I find a significant and negative effect of mining activity as measured by the mining activity index on both area and share of tree cover. This is different from Models 3 and 4, where there was no significant effect on the area covered by trees. Signs and significance of the coefficients associated with all control variables remain unchanged.

	Dependent variable:					
	Tree Cover Area	Tree Cover Pct.	Tree Cover Area	Tree Cover Pct.	Tree Cover Area	Tree Cover Pct.
	(1)	(2)	(3)	(4)	(5)	(6)
Mine (Dummy)	-0.063^{***} (0.007)	-0.009^{***} (0.001)				
Mining Activity			0.0004 (0.0005)	-0.0002^{**} (0.0001)	-0.005^{***} (0.001)	-0.0004^{***} (0.0001)
Expenditure	0.00004^{***} (0.00000)	0.00000^{***} (0.00000)	0.00004^{***} (0.00000)	0.00000^{***} (0.00000)	0.00003^{***} (0.00000)	0.00000^{***} (0.00000)
Expected Schooling	0.002 (0.004)	0.003^{***} (0.001)	0.002 (0.004)	0.003^{***} (0.001)	0.003 (0.004)	0.003^{***} (0.001)
Life Exp. at Birth	0.025^{***} (0.004)	0.001^{**} (0.001)	0.025^{***} (0.004)	0.001^{**} (0.001)	0.026^{***} (0.004)	0.001^{**} (0.001)
C/R FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,587	5,587	5,587	5,587	5,576	5,576
R^2	0.036	0.022	0.020	0.009	0.036	0.012
Adjusted R^2	-0.065	-0.080	-0.083	-0.095	-0.065	-0.091
F Statistic	46.995^{***} (df = 4; 5059)	28.571^{***} (df = 4; 5059)	25.242^{***} (df = 4; 5059)	10.907^{***} (df = 4; 5059)	46.899^{***} (df = 4; 5049)	15.811^{***} (df = 4; 5049)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 1: Regression results. The models are numbered the same as in Section 4.

Due to the difference in approaches, these results cannot be compared directly with the findings from some of the works cited in Section 2. Both investigate the direct effect of mining activity as a share of total deforestation, either by identifying deforestation events and assigning a driver to them based on visual interpretation (Austin et al., 2019) or by analyzing deforestation within areas zoned for different deforestation-driving purposes (Abood et al., 2015). The results of this analysis are designed to entail the total effect of mining activity based on deforestation, but cannot numerically be compared to the entire area of forest lost in Indonesia in a given period.

6 Limitations and Further Questions

The major limiting factor in answering the question of how and how strongly mines influence deforestation activities in Indonesia is finding an appropriate measure of mining activity. Future work could, e.g., make use of an expanded dataset similar to that of Maus et al. (2020) that offers an account of how mine areas changed year over year. The question treated here could then be analyzed again—this time with mining area used as independent variable instead of a mining activity index constructed from two different sources. In addition to the main independent variable of concern, there is considerable room for improvement of the set of control variables chosen. My selection of control variables is as much a result of reasoning as it is one of data availability, as data detailed to the level of Indonesian municipalities is relatively scarce. A path for further improvement on this would be to use remotely sensed, gridded measures of economic development, such as an account of the relative importance of agriculture to a municipality's economy, which would allow to directly account for farming-induced deforestation.

In addition to the data side of things, there are also different methodological approaches that could be applied to this type of question. One especially interesting addition to the model used would be controlling for spatial spillovers, similar to the approach used by Kuschnig et al. (2021). That way, it would become possible to distinguish the direct and indirect effect of mining activity on forest loss, which would enable an analysis comparable to that from Sonter et al. (2017). However, this is both a methodological question and an issue of data availability, as it would require data on the extent of mines over time rather than just an activity index.

7 Conclusion

About half of Indonesia is covered in tropical forest, an ecosystem that fulfills a multitude of functions for both economy and environment. As Indonesia's economy continues to grow, development and conservation are put at odds. In addition to decades of oil palm plantations as well as the timber and logging industries, the growing mining industry relies on exploiting formerly forest-covered land, a practice that endangers thousands of species and frees up large amounts of carbon stored in the forest's soil and plants.

Using remotely sensed data on land use and locations of mines as well as night light emissions as a proxy for activity at a mine, I found a significant negative effect of increased mining activity both on the area and the share of a city or regency covered by forest. This activity—as well as its effects—are most obvious in the region of Kalimantan. Further research is required to exactly quantify the importance of mining on deforestation, especially its indirect effects that have not been captured by previous research that focused on direct transformation. However, the results show clearly that mining activity plays a role in loss of Indonesian rainforest cover.

While this is unsurprising, it serves as confirmation that the country's forests remain at risk even after increased political, public, and legal attention to agricultural practices. After decades of accelerating forest loss, Indonesia has committed to not only slow, but halt net deforestation by 2030. Success to do so may not only save one of the world's most important ecosystems, but could also provide an opportunity for Indonesia to build a sustainable economy that makes use of the country's vast resources without threatening their further use.

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