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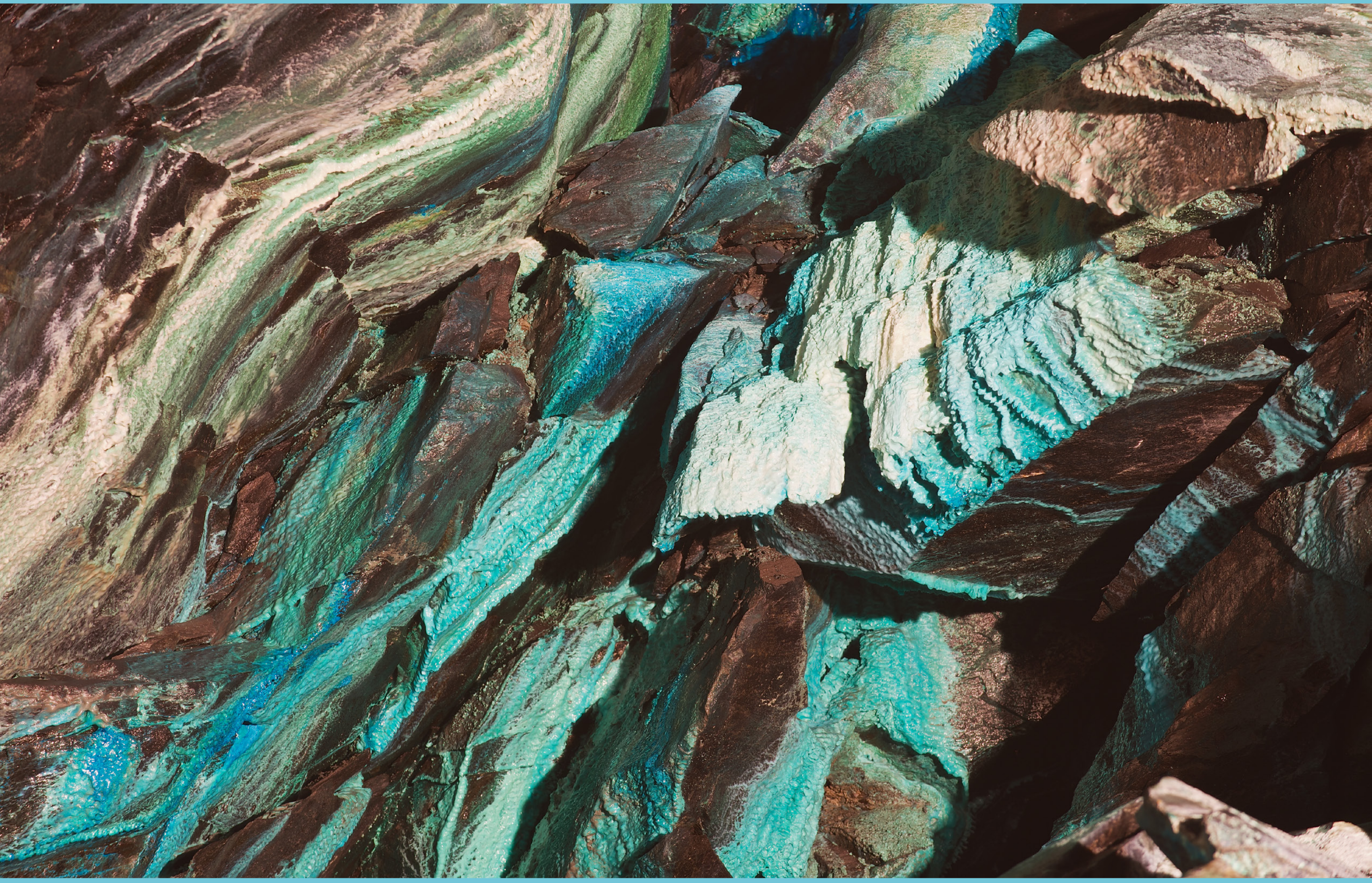
THE IMPACT OF MINING ON LOCAL COMMUNITIES



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INTRODUCTION

Global mineral demand is expected to increase dramatically in the coming decades. Minerals are used extensively in clean energy technologies, which are advancing because of regulatory and free market factors. Many national governments have enacted policies supporting the displacement of fossil fuels by carbon-free energy, and technological advances in solar, wind, and battery technologies have made these energy sources cost-competitive. At the same time, the electrification of transportation and other activities, along with the rise of artificial intelligence and explosive growth in data centers, are powerful drivers of rising electricity demand, which will likely be met primarily with carbon-free energy. The International Energy Agency (IEA) projects that total mineral demand from clean energy technologies will double by 2040 under current policies and quadruple under policies consistent with reaching net-zero carbon emissions.[1]

Of particular importance are "critical minerals" that serve an essential function in one or more energy technologies and are at high risk of supply chain disruption.[2] Critical minerals are used in several clean energy technologies, including solar panels, wind turbines, and transmission lines. Lithium-ion batteries are the most important technology for mineral demand, largely because they are critical components in nearly all electric vehicles (EVs) manufactured today. Batteries are also experiencing a recent surge in deployment on electricity grids, where they are paired with solar and wind generation to store carbon-free energy during times of day when these sources are abundant and discharge when they shut down. These "grid-scale batteries" will likely be key in overcoming the intermittency of solar and wind and providing 24/7 carbon-free electricity.

Global production of critical minerals is expected to increase modestly in the coming years,[3] but much more investment in exploration and development of new deposits will be needed to meet demand. While this increased mining activity is imperative for addressing climate change, it also raises environmental problems of its own. Large-scale mining can cause deforestation and other types of habitat destruction. It can leak toxic chemicals into the surrounding soil and water, and water-intensive mining methods can deplete local water supplies. Balancing the economic and carbon-reducing benefits of mines with their environmental impacts on local communities will be a crucial component of the clean energy transition.

This report examines certain economic and environmental impacts of the mining of critical minerals on areas near large-scale mining projects in developing countries. We estimate the effects of mining on three outcomes: economic activity, deforestation, and agricultural output.

Mining can affect the local economy in several ways. There is the direct impact of capital and labor deployment at or near the mining site itself. There may also be "spillovers" from mining activity to geographically nearby areas, driven by upstream/downstream linkages in the mining supply chain or workers moving to a city within commuting distance of the mine.

Mining can lead to deforestation through various mechanisms. Most directly, forests are cleared for equipment and infrastructure at the extraction site. However, some studies have found that deforestation occurs well beyond mining lease boundaries because of road construction, urban expansion of mining towns, and other factors.[4]

In addition, mining can reduce farm yields because of changes in land use and environmental damage. Mines generate various air, land, and water pollutants that can degrade the productivity of nearby farms.[5] Some mining methods use extremely high volumes of water and may compete with nearby farms for scarce water resources.[6] Mining is predominantly located in rural areas, where the majority of households in developing countries depend on the agricultural sector. Any reductions in farm productivity would offset at least some of the economic gains generated by mining.

We find that in developing countries as a whole, large-scale mining production is associated with higher economic activity, increased deforestation, and mixed effects on farm yields. We separately estimate effects for sub-Saharan Africa (SSA), Latin America and the Dominican Republic (LADR), and East Asia. SSA, while seeing positive effects on economic activity, experienced the most negative impacts of the three regions with regard to both deforestation and farm yields. LADR fared best, with the largest positive effects on economic activity, no significant effects on deforestation, and positive effects on farm yields (note that this farm yields result is largely driven by a cluster of mines in a region of Brazil where agricultural productivity has grown rapidly—see the results section below for further discussion). East Asia did not experience significant effects on economic activity or farm yields but did see increased deforestation as a result of mining.

After evaluating economic and environmental effects of large-scale mining in general, we separately evaluate the impacts of three of the most important critical minerals: copper, nickel, and cobalt.[7] Copper, as a highly conductive and durable material, is a major component in batteries, solar and wind generation, and electricity transmission networks. Copper is already one of the most highly demanded minerals in the world, but clean energy technologies will further drive demand in the coming decades. Nickel and cobalt are both used in cathodes in the majority of EV batteries. The IEA projects demand for both minerals to roughly double between 2023 and 2050.[8]

We find that all three of these critical minerals generally have large positive effects on local economic activity. However, nickel mining is associated with substantially lower farm yields. Cobalt mining, which is concentrated in SSA, is associated with large and significant negative effects for both deforestation and farm yields.

This report provides a broad global overview of the local impacts of modern large-scale mining. It is important to note that we estimate the *average* historical effects of many mines around the world, and the impact of any particular mine can vary widely in either direction. This is a global exploration of overall impact that can lead to interesting case studies of individual countries or mining projects.

DATA AND METHODOLOGY

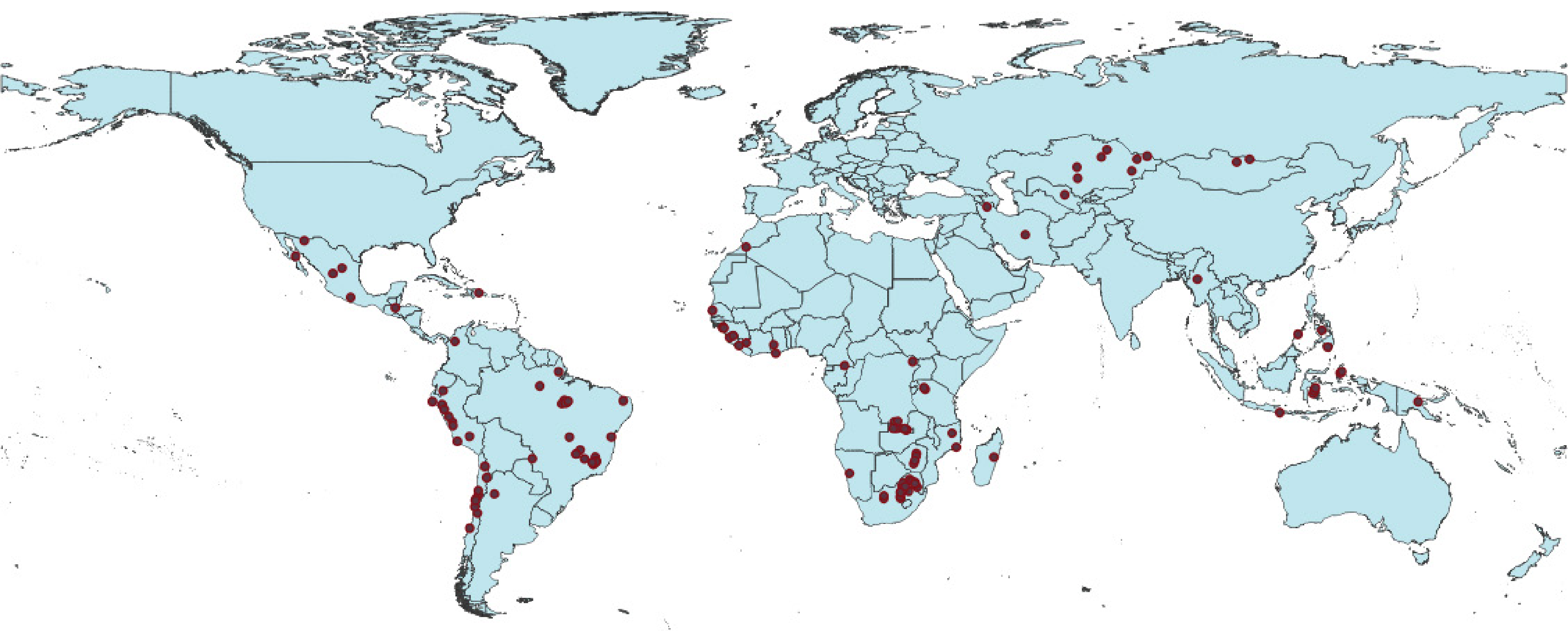
We evaluate the effects of large-scale mining on three outcome variables detailed in this section: night-time luminosity (a proxy for economic activity; see Technical Appendix), probability of a significant deforestation event, and average staple crop yields. For all three outcomes, we estimate the impacts of mine openings using a "difference-in-differences" model. This method compares outcomes between a "treatment" group (areas with large-scale mining) and a "control" group (areas with no large-scale mining) before and after mining begins. Average differences in outcomes that exist prior to mining are used as a baseline, and larger or smaller average differences that arise after mining begins are interpreted as the treatment effect—that is, the result—of mining.[9] Our empirical strategy also accounts for any within-country common trends that are not directly related to mining (see Technical Appendix).

We define large mines as those in the top 15 percent of mineral resources and reserves[10] by monetary value among all mines that began production between 1980 and 2020 (which roughly correspond to the first and last years of our combined data sources). The 15 percent threshold captures at least an 80 percent share of global resources for each of the major critical minerals we consider, while also limiting the group of treatment mines to very large, productive deposits.

The direct local economic impacts of mining activity in developed countries are likely to be smaller, on average, than those in developing countries, where mining can make up a large share of regional economies. In addition, environmental impacts are likely to be more severe in countries with weaker administrative states and regulations. Given these differing contexts, and the fact that the vast majority of mining production has come from developing countries during our sample period, we only consider countries not classified as "high income" by the World Bank.[11] We also do not include China in our analysis because information on reserves for Chinese mines is generally unavailable from our data sources.

Figure 1 shows the locations of all large-scale productive mines included in our analysis. Thirty-four countries have at least one treatment mine. Table 1 presents summary statistics for these countries (grouped by regions), showing the number of treatment mines, gross domestic product (GDP) per capita, percentage of land covered by forest, and percentage of land used for agriculture. The number of treatment mines corresponds to mines that are included in the sample for any of the three outcomes that we study. Because these samples differ by time period and other restrictions, a given mine may be included for only certain outcomes.

Figure 1: Treatment Mine Locations



Source: Data from S&P Global (2025)

Table 1: Summary Statistics for Mining Countries

1a. Sub-Saharan Africa

Country	Treatment mines	GDP per capita (2022 USD)	Forest land %	Ag. land %
Cameroon	1	1,605	42.8%	20.6%
Congo, Dem. Rep.	3	643	54.7%	15.5%
Ghana	2	2,240	35.2%	55.4%
Guinea	3	1,417	24.9%	70.0%
Liberia	2	745	78.5%	20.0%
Madagascar	1	497	21.3%	70.3%
Mozambique	2	578	46.1%	52.7%
Namibia	1	4,349	7.9%	47.1%
Senegal	1	1,565	41.5%	49.4%
Sierra Leone	2	860	34.6%	54.7%
South Africa	24	6,523	14.0%	79.4%
Tanzania	2	1,208	50.6%	44.6%
Zambia	6	1,447	59.8%	32.1%
Zimbabwe	4	2,041	44.9%	39.5%

1b. Latin America and the Dominican Republic

Country	Treatment mines	GDP per capita (2022 USD)	Forest land %	Ag. land %
Argentina	1	13,936	10.4%	43.4%
Bolivia	1	3,644	46.5%	35.8%
Brazil	26	9,281	59.1%	26.7%
Chile	9	15,451	24.8%	14.3%
Colombia	1	6,675	52.9%	37.6%
Dominican Republic	1	10,110	44.8%	50.4%
Ecuador	1	6,541	49.8%	21.5%
Guatemala	1	5,358	32.7%	43.0%
Mexico	5	11,385	33.7%	49.4%
Peru	9	7,363	56.2%	19.1%

1c. East Asia

Country	Treatment mines	GDP per capita (2022 USD)	Forest land %	Ag. land %
Indonesia	6	4,731	48.0%	29.8%
Mongolia	2	4,994	9.1%	71.9%
Myanmar	1	1,158	42.8%	19.9%
Papua New Guinea	1	3,102	79.0%	3.1%
Philippines	3	3,548	24.3%	42.5%

1d. Other Regions

Country	Treatment mines	GDP per capita (2022 USD)	Forest land %	Ag. land %
Iran	2	4,405	6.6%	29.0%
Kazakhstan	7	11,255	1.3%	79.4%
Morocco	1	3,455	12.9%	67.9%
Uzbekistan	1	2,579	8.5%	58.5%

Data Sources: S&P Global (2025), World Development Indicators (2025)

We analyze outcomes before and after the year a major mine begins production, as indicated by S&P Global. When a geographic unit is exposed to multiple major mine openings, we consider the first such opening as the year of treatment. If the first major mine opening occurs before our sample period begins, we drop the unit from the sample.

For the luminosity and deforestation outcomes, we first analyze the full sample to find effects for developing countries overall. We then perform separate regional analyses for LADR, SSA, and East Asia because these three regions contain the vast majority of large-scale mines in our sample. For farm yields, we only perform regional analyses because our yield data are crop-specific and different regions primarily grow different crops—maize for LADR and SSA and rice for East Asia.

We also perform separate analyses for three of the most important critical minerals: copper, nickel, and cobalt. For copper and nickel, we restrict treatment mines to those where copper or nickel is the primary commodity, respectively. For cobalt, we restrict treatment mines to those that produce any cobalt, whether or not it is primary. We use this approach because cobalt is the primary commodity for few large mines, but it is often a significant secondary commodity for copper, nickel, or platinum mines. Therefore, most of the global cobalt production comes from mines where it is a secondary commodity.

The geographic units considered in our analyses differ across the three outcome variables because of differences across data sources. For luminosity, the geographic unit of analysis is the level 2 administrative district (e.g., counties in the US). A district is included in the treatment group if its first productive large mine began operations within its borders between 1993 and 2013, coinciding with the range for our lights data.

For farm yields and deforestation, we use 0.5 x 0.5 degree cells as the unit of analysis (0.5 degrees is roughly 35 miles at the equator). However, the treatment groups differ because of the different time periods covered by the yields and deforestation datasets. For farm yields, a cell is included in the treatment group if its centroid is within 50 kilometers (km) of a large mine that began production between 1982 and 2015. For deforestation, a cell is included if its centroid is within 50 km of a large mine that began production between 2001 and 2019.

For economic activity and farm yields, our dependent variables are the natural log of luminosity and the natural log of average farm yield within each district/cell. We therefore analyze percentage changes (as approximated by unit changes in natural logs) in luminosity and farm yields. The dependent variable for the analysis of deforestation is an indicator for whether the cell experienced a major loss of tree coverage in at least 1 percent of the area within the cell that contained trees as of 2000. For further details on the sources, sample selection, and methods used to define our outcome variables, see the Technical Appendix.

RESULTS

Overview of Main Results

We find that large-scale mining, on average, significantly increases economic activity while also significantly impacting deforestation and farm yields. Moreover, we find important regional differences in the distribution of the positive and negative impacts of large-scale mining.

The positive economic effects of large-scale mining are concentrated in SSA and LADR, while no effects are found for East Asia. Critical minerals (i.e., copper, cobalt, and nickel) specifically are found to increase economic activity in these regions in magnitudes similar to that of mining overall, although we find no evidence that these effects spill over into surrounding districts.

In terms of environmental impacts, we find evidence that large-scale mining significantly increases the rate of deforestation in the area within 0–50 km of the mine, and these effects are concentrated in SSA and East Asia. Focusing on specific minerals, we find that cobalt mining has especially damaging effects on nearby forests. In addition, mines tend to impact deforestation beyond the 50 km threshold, as we find deforestation effects in areas up to 100 km from the mines.

Finally, there is mixed evidence on the impact of large-scale mining on farm yields. We find that mining has significant negative impacts on farm yields within 50 km in SSA, but find positive effects in LADR (as discussed further below, these positive effects are primarily driven by a cluster of mines in an area of Brazil that experienced strong overall agricultural productivity growth during our sample period). For both regions, these impacts extend to areas within 50–100 km of the mines. In SSA, nickel mines have particularly negative effects, while cobalt mines are also harmful. Nickel mines likewise significantly reduce rice yields in East Asia.

Mining Effects on Local Economic Activity

We find that large-scale mineral production statistically significantly increases economic activity within the mining district (see Table 2). In our full sample (which includes all developing countries), the start of mining production is associated with an increase in luminosity of 25.6 percent. These effects are concentrated in SSA and LADR, while there is a small and statistically insignificant impact in East Asia.[12]

Using findings from prior studies of the relationship between luminosity and GDP, we estimate that the effect on GDP from large-scale mining is approximately 7.7 percent for the full sample of developing countries.[13] That is, the opening of a large-scale mine increased GDP by an average of 7.7 percent for any year after the mine opened compared to what it would have been if no mine had opened.

Table 2: Mining Effects on Luminosity

	Coefficient	N
All countries	0.256***	343,618
SSA	0.318***	27,764
LADR	0.346***	181,280
East Asia	.017	30,118

*Notes: Dependent variable: ln(lights/capita). *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), National Oceanic and Atmospheric Administration (2013)

Table 3 presents the results when limiting the mines to those producing certain critical minerals. Copper-, nickel-, and cobalt-producing mines all have large and positive effects on economic activity, although the estimate for nickel is not statistically significant.[14]

Table 3: Mining Effects on Luminosity for Selected Critical Minerals

	Coefficient	N
Primary copper	0.215*	342,716
Primary nickel	0.284	342,430
Contains cobalt	0.285**	342,562

*Notes: Dependent variable: ln(lights/capita). *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), National Oceanic and Atmospheric Administration (2013)

In Table 4, we show estimates of geographic spillovers of mining on economic activity in nearby districts. To obtain these estimates, we define the treatment group as all districts bordering a district with a large productive mine but not containing a mine itself.[15] Table 4 shows that, on average, economic impacts are limited to districts containing mines. For the full sample, there are no significant impacts of bordering mines. When separating by region, we find no impacts for SSA and LADR and a negative effect for East Asia (albeit only statistically significant at a 10 percent level).

Table 4: Mining Effects on Luminosity for Bordering Districts

	Coefficient	N
All countries	0.033	342,342
SSA	0.002	27,324
LADR	0.032	180,950
East Asia	-0.269*	29,986

*Notes: Dependent variable: ln(lights/capita) for districts bordering a mining district. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), National Oceanic and Atmospheric Administration (2013)

Mining Effects on Deforestation

We find that large-scale mining statistically significantly raises the probability of major tree loss (see Table 5). For the full sample of non-high-income countries, large-scale mining raises the probability of a major tree loss event for cells within 50 km of a mine by 5.7 percentage points. In other words, large-scale mines caused nearby major tree loss events to be 5.7 percentage points more likely on average after the mine opened than would have been the case if no mine had opened. The sample average probability of major tree loss in a given year is 10.7 percent, so being near a producing mine increases this probability by greater than 50 percent. We again find notable differences among world regions. The impact on deforestation is especially large in SSA and statistically significant in East Asia.

We do not find evidence of deforestation effects for LADR. This result may seem surprising and contrasts with some past studies,[16] which find that mining increases local deforestation in the Amazon rainforest. This result does not imply that tree loss is not occurring near large mines in LADR. Rather, it reflects the fact that, in our sample, forest loss rates (as measured in this study) are higher in LADR than in any other region in the world—for both cells that are near mines and those that are not.

Deforestation rates are especially high in Brazil, which contains over half of the cells near mines in our LADR sample. However, mining is just one factor driving Amazon depletion and not the most important one. A World Bank analysis estimated that 80 percent of converted Amazon forest land was used for agricultural expansion,[17] particularly soybean cultivation and cattle ranching. Our empirical method compares changes in forest cover near mines to changes not close to mines (within the same country). Because deforestation rates in the Amazon and elsewhere in LADR are so high due to other factors, our regressions likely cannot statistically distinguish deforestation directly caused by mining.

Table 5: Mining Effects on Deforestation

	Coefficient	N
All countries	0.057***	361,960
SSA	0.094***	111,720
LADR	-0.007	119,080
East Asia	0.095**	86,980

*Notes: Dependent variable: Major tree loss event probability for cells within 50 km of large-scale mine. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), Hansen/UMD/Google/USGS/NASA (2013)

Cobalt mining, which is concentrated in SSA, is particularly damaging to forests (see Table 6); our estimate implies that the probability of a major tree loss in a given year is 17.1 percentage points higher when near a cobalt mine. We did not find that copper mining was associated with higher rates of tree loss. Nickel mining has a large effect size, although it is not statistically significant.

Table 6: Mining Effects on Deforestation for Selected Critical Minerals

	Coefficient	N
Primary copper	0.008	359,800
Primary nickel	0.122	359,520
Contains cobalt	0.171***	359,600

*Notes: Dependent variable: Major tree loss event probability for cells within 50 km of large-scale mine. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), Hansen/UMD/Google/USGS/NASA (2013)

We find evidence of deforestation effects extending beyond the 50 km radius cell containing mines (see Table 7). For the full sample of non-high-income countries, we find that major tree loss is 4.5 percentage points more likely within 50–100 km of a large producing mine, smaller than the estimate for within 50 km but still statistically significant. The impact for SSA is similarly smaller but still statistically significant. For LADR, we find a statistically significant increase in probability of tree loss, compared to no effect within 50 km. Conversely, the impact for East Asia is much smaller than that for 0–50 km and is no longer statistically significant.

Table 7: Mining Effects on Deforestation for Cells Within 50–100 km of Mine

	Coefficient	N
All countries	0.045***	356,020
SSA	0.070***	109,440
LADR	0.033*	117,060
East Asia	0.017	71,200

*Notes: Dependent variable: Major tree loss event probability for cells within 50–100 km of large-scale mine. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), Hansen/UMD/Google/USGS/NASA (2013)

Mining Effects on Farm Yields

Large-scale mining has effects on farm yields that differ between the three regions we analyze (see Table 8).[18] In SSA, mining has a statistically significant negative impact on maize yields. The estimate implies that mining is associated with a negative 5.1 percent effect on average yields within 50 km of a large mine. That is, large-scale mines decreased nearby yields on average by 5.1 percent after the mine opened compared to what they would have been if no mine had opened. Conversely, in LADR, we find that mining is associated with a 3.1 percent positive effect on maize yields. This counterintuitive result is driven primarily by Brazilian mines, especially a cluster of mines in the state of Minas Gerais, where agricultural productivity has grown strongly in spite of its mining activity.[19] We do not find any significant effect in East Asia.

Table 8: Mining Effects on Farm Yields

	Coefficient	N
Maize yield, SSA	-0.051***	139,657
Maize yield, LADR	0.031**	98,385
Rice yield, East Asia	-0.004	89,037

*Notes: Dependent variable: ln(tons/hectare) of specified crop. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), Iizumi and Sakai (2020)

In addition to differing regional effects, we find notable variation in effects on farm yield that depends on the critical mineral analyzed (see Tables 9, 10, and 11). The effects for copper mining are not statistically significant in any of the three regions, while the effects for nickel and cobalt mining are negative and statistically significant. Nickel mining has a large and significant negative impact on yields in SSA and East Asia, though these results are driven by a few countries with large nickel mines in the regions (Madagascar and South Africa in SSA, and Indonesia in East Asia).[20] Cobalt mining has a smaller but statistically significant negative effect on yields in SSA.

Table 9: Mining Effects on Farm Yields for Selected Critical Minerals, SSA

	Coefficient	N
Maize yield, primary copper	-0.034	137,628
Maize yield, primary nickel	-0.090***	137,329
Maize yield, contains cobalt	-0.033*	137,913

*Notes: Dependent variable: ln(tons/hectare) of specified crop. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), Iizumi and Sakai (2020)

Table 10: Mining Effects on Farm Yields for Selected Critical Minerals, East Asia

	Coefficient	N
Rice yield, primary copper	-0.009	88,968
Rice yield, primary nickel	-0.053***	88,857

*Notes: Dependent variable: ln(tons/hectare) of specified crop. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively. No treatment mines containing cobalt are located near agricultural land in East Asia region.*

Source: S&P Global (2025), Iizumi and Sakai (2020)

Table 11: Mining Effects on Farm Yields for Selected Critical Minerals, LADR

	Coefficient	N
Maize yield, primary copper	0.056	97,481

*Notes: Dependent variable: ln(tons/hectare) of specified crop. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively. No treatment mines containing nickel or cobalt are located near agricultural land in LADR region.*

Source: S&P Global (2025), Iizumi and Sakai (2020)

Table 12 presents farm yield estimates for cells that are within 50–100 km of a large-scale mine. Similarly to deforestation, in SSA the negative effect is smaller than that for districts within 50 km of the mines, but the effect is still statistically significant. In LADR, similarly to the 0–50 km range, the effect on maize yields is positive and significant. We again find no effect on rice yields for East Asia.

Table 12: Mining Effects on Farm Yields for Cells Within 50–100 km of Large-Scale Mine

	Coefficient	N
Maize yield, SSA	-0.039**	136,951
Maize yield, LADR	0.045**	96,892
Rice yield, East Asia	0.005	88,788

*Notes: Dependent variable: ln(tons/hectare) of specified crop. *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.*

Source: S&P Global (2025), Iizumi and Sakai (2020)

CONCLUSIONS

Global demand for minerals is poised to rise sharply and persistently for the foreseeable future. The clean energy transition and explosive growth in data centers are driving demand for carbon-free electricity, which in turn relies on critical minerals for a variety of decarbonization technologies. At the same time, many commentators have raised concerns about the environmental costs of increased mining and its impact on local communities. Our report presents evidence that can help manage these tradeoffs.

We find that, on average, large mine openings have substantially increased economic activity within the mining district, especially in LADR and SSA. But these economic benefits often came with environmental costs. Major deforestation events near mines became significantly more likely after production began. Deforestation effects were concentrated in SSA and East Asia and were more severe for cobalt mines. Further, mining decreased average farm yields in the surrounding area in SSA, though mining was associated with increased yields in LADR. Nickel and cobalt mines were found to be particularly harmful to farm yields.

Many mining companies, recognizing the need to reduce the sector's environmental impact, are investing in more sustainable mining practices. These include pollution-capturing technologies, water recycling, on-site clean power generation, and various technologies for recovering minerals from mining waste. Committing to greater engagement with communities surrounding mining projects to utilize these processes and ensure best practices will be crucial for meeting global mineral demand while minimizing harm.

TECHNICAL APPENDIX

Regression Specification

All regressions in this report use the following estimating equation:

$$Y_{it} = \alpha + \beta^{*}post\_mine_{it} + \mu_i + \delta_{ct} + \varepsilon_{it}$$

Where Y_{it} is the outcome of interest (luminosity, tree loss, farm yields) for location *i* in year *t*. $post\_mine_{it}$ is an indicator equal to one if the observation is near a mine after the mine has begun production, and zero otherwise. μ_i is a set of country fixed effects, and δ_{ct} are country-by-year fixed effects. These fixed effects control for any fixed characteristics of geographic units and any year-specific factors that are common within a given country.

We therefore estimate treatment effects based on how outcomes evolve for units near a large mine before and after the mine opens, compared to units within the same country without a large mine nearby. Standard errors are clustered at the district level for the luminosity outcome and the grid cell level for deforestation and farm yields.

Data and Methodology for Night-Time Lights

DATA

Night-time luminosity captured by satellite images has been demonstrated to be a high-quality proxy for measuring GDP levels and growth.[21] Prior studies have found that approximately 76 percent of the within-country variation in GDP can be predicted by variation in total luminosity. Like public GDP data, luminosity data provide an annual, globally comparable measure of economic activity. But because it is measured at a high resolution, luminosity data enable researchers to measure activity for smaller geographic units than traditional GDP data, which are often only available at the national level. In this study, we measure luminosity within level 2 administrative districts (e.g., counties in the US).

Night-time lights data for 1992–2013 are provided by the National Oceanic and Atmospheric Administration. The data are annual averages of luminosity readings from meteorological satellites, after filtering for cloud coverage and other ephemeral light sources. The value for a given pixel-year ranges from 0 (no detectable lights) to 63. These readings are provided in a global grid of 30 x 30 arc-second pixels (about 1 square km at the equator).

METHODOLOGY

For our luminosity regression, the geographic unit of analysis is the level 2 administrative district (e.g., counties in the US). Prior studies have found that local economic shocks tend to spread within a political district.[22] Governments may tax mining output and spend the proceeds in other parts of the district, and mining workers may live in a nearby city that is not immediately proximate to the mine but within commuting distance.

A district is in the treatment group if its first productive large mine began operating within its borders between 1993 and 2013 (our lights data range from 1992 to 2013, which ensures at least one observation before and after production for each treated district that is necessary for our difference-in-differences method to work[23]).

The dependent variable is the natural log of the sum of luminosity readings within the district. We are therefore analyzing percentage changes in luminosity. We exclude a district from the sample if it has any observation during the sample period where the sum of lights readings is less than 100. We use this approach because districts with very low luminosity can experience changes in lights that are relatively small in practical terms but extreme when expressed in percentage terms, which can distort regression results.

Data and Methodology for Farm Yields

DATA

Annual farm yields data from 1981 to 2016 come from the Global Dataset of Historical Yield (GDHY), which is described in Iizumi et al. (2019).[24] The GDHY provides annual estimates of average yields for four staple crops (maize, wheat, rice, soybeans) for a global grid made up of 0.5 x 0.5 degree cells (0.5 degrees is approximately 35 miles at the equator).

METHODOLOGY

We use the GDHY's 0.5 x 0.5 degree cells as the unit of analysis to analyze farm yields. A cell is in the treatment group if its centroid is within 50 km of a large mine that began production between 1982 and 2015.

The dependent variable is the natural log of the average yield within a cell, which is measured in tons harvested per hectare of land dedicated to a given crop. We limit the sample to cells with at least one year where the yield value exceeds one (this eliminates roughly 9 percent of cells in the original sample of cells containing any staple crop cultivation). Similarly as in the case of luminosity, we use this approach to prevent distortionary effects of cells with extremely low yields.

Data and Methodology for Tree Loss

DATA

Deforestation data from 2000 to 2020 come from the "Global Forest Change" dataset described in Hansen et al. (2013).[25] These data are derived from algorithmic processing of high-resolution (roughly 31 x 31 meters) satellite image data. We use two parts of the dataset: first, a measure of percentage canopy closure for a given pixel for all vegetation higher than 5 meters. Second, an indicator of the year a given pixel experienced a "gross forest cover loss event," changing from a forest to a non-forest state.

METHODOLOGY

Our unit of observation is the same 0.5 x 0.5 degree cells as in the farm yields analysis. The tree data, however, come in much higher resolution, so that each cell contains 4 million pixels of tree data. To exclude cells with zero or trivial tree coverage, we select our overall sample as cells that contain at least 100,000 pixels of non-zero tree coverage at the start of the sample period (year 2000), which is roughly two-thirds of all cells. A cell is in the treatment group if its centroid is within 50 km of a large mine that began production between 2001 and 2019.

The dependent variable is an indicator for whether the cell experienced a major loss of tree coverage in at least 1 percent of its pixels that contained trees in 2000. This threshold represents a significant loss of trees, occurring in just greater than 10 percent of all sample observations.

ENDNOTES

1. "Mineral Requirements for Clean Energy Transitions," International Energy Agency, accessed July 9, 2025, https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/mineral-requirements-for-clean-energy-transitions.

2. "What Are Critical Materials and Critical Minerals?" US Department of Energy, accessed July 9, 2025, https://www.energy.gov/cmm/what-are-critical-materials-and-critical-minerals.

3. *Global Critical Minerals Outlook* 2025 (International Energy Agency, May 2025), https://www.iea.org/reports/global-critical-minerals-outlook-2025.

4. J. Mwitwa, L. German, et al., "Governance and Sustainability Challenges in Landscapes Shaped by Mining: Mining-Forestry Linkages and Impacts in the Copper Belt of Zambia and the DR Congo," *Forest Policy and Economics* 25 (December 2012): 19–30, https://doi.org/10.1016/j.forpol.2012.08.001; Laura J. Sonter, Diego Herrera, et al. "Mining Drives Extensive Deforestation in the Brazilian Amazon," *Nature Communications* 8.1 (October 18, 2017): 1013.

5. Fernando M. Aragón and Juan Pablo Rud, "Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana," *The Economic Journal* 126.597 (September 21, 2015): 1980–2011, https://academic.oup.com/ej/article-abstract/126/597/1980/5077962.

6. "Does Copper Mining Use a Lot of Water?" Enviroliteracy, June 9, 2024, https://enviroliteracy.org/does-copper-mining-use-a-lot-of-water/.

7. Because of data constraints, we do not focus on other critical minerals such as lithium, graphite, and rare earths. Lithium mining is concentrated in a relatively small number of mines, many of which are in developed countries; this report is focused on the developing world. Rare earths and graphite production are overwhelmingly concentrated in China, which is excluded from this study because of a lack of mine-specific data.

8. *Global Critical Minerals Outlook* 2025.

9. It is possible that some economic and environmental impacts may begin in the run-up to production because of mine construction and associated activities. In a study of mining in sub-Saharan Africa, Nemera Mamo et al., "Intensive and Extensive Margins of Mining and Development: Evidence from Sub-Saharan Africa," *Journal of Development Economics* 139 (June 2019): 28–49, https://www.sciencedirect.com/science/article/abs/pii/S0304387818303936, found modest luminosity effects beginning two years before the first year of production. To the extent that impacts begin before production, our impact estimates would be biased toward zero and could therefore be thought of as lower-bound estimates.

10. A *resource* is a concentration of minerals with a reasonable economic prospect of being mined, while a *reserve* has been demonstrated to be economically viable via a feasibility study.

11. As of this writing, Chile is classified as a high-income country, but it was not for most of our analysis period. Therefore, we include Chile in our analysis.

12. For the lights sample, East Asia has only six treatment mines due to restrictions on mine opening timing and minimum light activity, as described in the Technical Appendix.

13. Vernon Henderson et al., “A Bright Idea for Measuring Economic Growth,” *American Economic Review* 101, no. 3 (May 3, 2011): 194–199, https://pmc.ncbi.nlm.nih.gov/articles/PMC4112959/, found that for low- and middle-income countries, the elasticity between the natural log of lights growth and GDP growth is approximately 0.3. Using this number, we can estimate that the effect on GDP from large-scale mining was .256x0.3 = 7.7%.

14. Because our luminosity data end in 2013, they predate much of the nickel investment boom in Indonesia, which now dominates global nickel production. Only four large-scale nickel mines are in this sample, which contributes to the estimate’s low statistical power.

15. For these regressions, we exclude any districts with a large mine from the analysis.

16. Stefan Giljum, Victor Maus, et al., “A Pantropical Assessment of Deforestation Caused by Industrial Mining,” *Proceedings of the National Academy of Sciences* 119.38 (September 20, 2022): e2118273119, https://pubmed.ncbi.nlm.nih.gov/36095187/; “Mining Drives Extensive Deforestation in the Brazilian Amazon.”

17. Sergio Margulis, *Causes of Deforestation of the Brazilian Amazon*, vol. 22. (World Bank Publications, 2004); Laura J. Sonter, Diego Herrera, Damian J. Barrett, Gillian L. Galford, Chris J. Moran, and Britaldo S. Soares-Filho, “Mining Drives Extensive Deforestation in the Brazilian Amazon,” *Nature Communications* 8, no. 1 (2017): 1013.

18. We do not analyze a full global sample of countries for farm yields because different crops are dominant in different regions.

19. “Minas Crops Produce Above the National Average,” Revista Cultivar, accessed July 23, 2025, https://revistacultivar.com/news/mine-crops-produce-above-the-national-average.

20. Latin America and the Dominican Republic do not have large-scale cobalt or nickel mining that started production during our sample period, so we analyze only copper in that region. We also exclude cobalt mining for East Asia.

21. Henderson et al., “A Bright Idea for Measuring Economic Growth.”

22. Mamo et al., “Intensive and Extensive Margins of Mining and Development.”

23. Note that there is often a significant lead time between mine discovery and production. Luminosity may also be affected by mine preparation activities prior to production. As a result, our estimates could be biased downward; therefore, the positive effects we find can be interpreted as a lower bound.

24. Toshichika Iizumi and Toru Sakai, “The Global Dataset of Historical Yields for Major Crops 1981–2016,” *Scientific Data* 7, no. 1 (2020): 97.

25. Matthew C. Hansen, Peter V. Potapov, Rebecca Moore, Matt Hancher, Svetlana A. Turubanova, Alexandra Tyukavina, David Thau et al., “High-Resolution Global Maps of 21st-century Forest Cover Change,” *Science* 342, no. 6160 (2013): 850–853.

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