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Detecting Critical Mines: A Perspective from the Sky

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Abstract

The increased geopolitical and geo-economic importance of critical minerals requires a clear and accurate understanding of the nature of supply. Without this understanding, analysis of a range of key economic and policy questions will be based on systematically biased evidence and hence risks misinforming policy. This paper uses state-of-the-art techniques combining satellite imaging and artificial intelligence to detect mines and build a global mining database. A comparison of "new" and "old" techniques to record mines indicates a significant gap in the form of missing mines. 'Missing mines' tend to be relatively small but can be found across a wide array of institutional settings and may be associated with multiple sources of misreporting. That said, there is some evidence that countries with higher shares of smaller missing mine exhibit lower control of corruption. The comprehensive nature of our database is helpful to revisit environmental, social and developmental spillovers stemming from the rapidly growing number of critical mines linked to critical mines.

Keywords: mine, satellite imagining, AI, critical minerals, economic development.

JEL Codes: O1, O4, O5, Q0.

I. Introduction

The global economy is undergoing simultaneous energy and digital transitions both reliant on technologies that require critical minerals.[1] Technologies including wind turbines, solar PVs, electricity networks, electric vehicles, magnets, and nuclear power require minerals such as copper, lithium, nickel, silicon, cobalt, rare earth elements, and uranium. Demand for these minerals is expected to grow quickly as the energy and digital transitions gather pace (IEA, 2021; IEA 2025).[2] In the face of this growth in demand, the relatively limited supply of critical minerals has triggered a race among economic superpowers, namely the United States, China and the European Union, over critical minerals especially these located in developing countries (Arezki and van der Ploeg, 2025).[3] This is evident from superpowers actively rolling out of strategies to secure access to critical mineral. Mines where critical minerals originate from are thus becoming centres of attention. Notwithstanding the absence of universal definition of what constitutes a mine[4], the stakes for accurate measurement of where mining activities occur have never been higher.[5] In this paper, we use state-of-the-art techniques combining satellite imaging and artificial intelligence to detect mines and build a global mining database.

The increased geopolitical and geo-economic importance of critical minerals requires a clear and accurate understanding of the nature of supply – its extent, spatial location and forms of production. Without this understanding, analysis of a range of key economic and policy questions will be based on systematically biased evidence, and hence risks mis-informing policy. Current methods for measuring the global distribution of mining activities, which tend to rely on self-reporting of financial information from formal sector firms, systematically mismeasure the extent of mining activities. However, advances in remote sensing, satellite imaging, large language models, and machine learning methods allow for a much more granular measurement.

The nature and extent of the gap between 'old' and 'new' measurement of mines may have radical consequences on our understanding of global mining and its consequences. The comprehensive nature of the database presented in this paper is helpful to revisit environmental,

[1] See: https://www.energy.gov/cmm/what-are-critical-materials-and-critical-minerals

[2] Forecasts suggest that demand for minerals for clean energy technologies will rise least four-fold by 2040 to meet climate goals, with pparticularly high growth for minerals needed for electric vehicles (IEA, 2021; IEA 2025).

[3] The latter are less industrialised and tend to consume fewer minerals than they produce.

[4] A holistic definition of a mine is a location where minerals are or have been extracted from the earth, evidenced by physical excavation, processing, or land modification—whether legal, illegal, artisanal, small-scale, industrial, active, or abandoned.

[5] See Berman et al. (2017), Von der Goltz et al. (2019), and Goldblatt et al. (2025) for a selection of papers investigating the effect of mines on respectively conflicts, health and wealth effects, as well as deforestation.

social and developmental spillovers stemming from the growing number of mines linked to critical minerals. Furthermore, accurate location information on where mining activity is pivotal in linking it to other geospatial data accurately, ranging from supply chains along transport corridors to climate hazards and conflict presence. A central contribution of this paper is to explore some of the applications using that new global dataset.

The extraordinary growth in demand for critical minerals is making the necessity to address the mismeasurement of mines even more pressing. Indeed, the growth in demand is putting upward pressure on prices and stimulating new critical mineral discoveries and mining activities around the world.[6] Whether it is for governments, non-government organisations and multinational firms, the social, environmental and economic consequences of mining activities are pervasive. In developing countries, the new "bonanza" from critical minerals presents opportunities but also important risks. A less fragmented and more transparent record of mining activities could strengthen governance structure especially in developing countries. The stakes both from an academic and policy perspectives are thus very high.

Despite the economic importance of mining and its multifaceted spillovers, the availability of truly comprehensive global mining data is limited. Existing records, whether from mining ministries, international bodies, or commercial datasets, most prominently S&P (the 'industry standard' data source) exhibit large gaps, additionally compounded by the large presence of illegal and informal activity in mining and vested interests that fundamentally limit the transparency of the mining and extractives sectors. A growing body of evidence suggests that global mining activity is substantially under counted. Many countries or companies report outdated or incomplete records. Importantly, artisanal and small-scale mining (ASM) is widespread and largely unreported. Add to that, illegal mining remains largely invisible in official statistics. A growing body of work shows evidence that ASM could be several times larger than the number of mines reported in official or available statistics using traditional detection techniques (Couttenier et al. 2022; Maus et al. 2020; Tang et al. 2023; Werner et al. 2019).

Reasons for mismeasurement are multiple. The different categories include:

- *Technology:* Absent other modern methods, reporting from formal mine owners is a plausible basis for measurement but it is clearly limited by, amongst other things, being restricted to 'reporting firms' (i.e. large size bias), and not being timely (there is a lag in

[6] See Arezki and van der Ploeg (2019) for discussion of the role of openness in driving mining discovery.

reporting financial information which may be problematic around mine closing and opening).

- *Weak state capacity and corruption of officials:* The weak capacity of states to conduct and keep record including of geological surveys will yield limited details on locations and nature of mines absent disclosure from third parties. Over and above issues of weak state capacity, corruption of state officials could lead to misreporting to capture the revenues from mines.
- *Strategic non-disclosure by private actors:* Besides the limitations linked to the state, mine owners and private operators may have a range of reasons for non-declaration or a desire to hide their operations (tax evasion, illegal labour arrangements, environmentally damaging activities, dodgy customers, etc…).
- *Other factors:* Remoteness of mining sites could also drive mismeasurement. Mines also frequently expand beyond permitted boundaries, new artisanal operations emerge rapidly in response to commodity price shifts, and abandoned industrial mines often host renewed informal extraction.

The result is a fragmented, incomplete global picture for mining activity when using traditional method for detection of mining sites. The revolution in technology across the past decades have opened doors for new approaches to a more comprehensive and accurate detection of mining sites. The substantial increase of high-resolution imagery and innovation in satellite-based optical instruments, paired with the rapid advances in artificial intelligence and Machine Learning, offer substantial pathways to analyse global imagery at scale and speed (Burke et al, 2021). In this paper, we provide a comparison of "new" and "old" techniques to record mines.

To illustrate the contribution of using state-of-the-art techniques to detect mines, it is useful to present examples of mismeasurement using old techniques as revealed from new techniques. Figure 1 below shows an example of a falsely detected mine in Zambia using old detection techniques. The dot in the forest corresponds to a location that S&P indicates as a mining location. The imagery is, however, visibly showing no trace of any mining activity even in the vicinity. Instead, Figure 2 shows in the Northwestern Province of Zambia a case of a mine detected by satellite imaging.[7] Yet, that mine is not listed in S&P. Figure 3 show another mine located in Bolivia in the region of La Paz which exists but is missing from the S&P record.[8] In

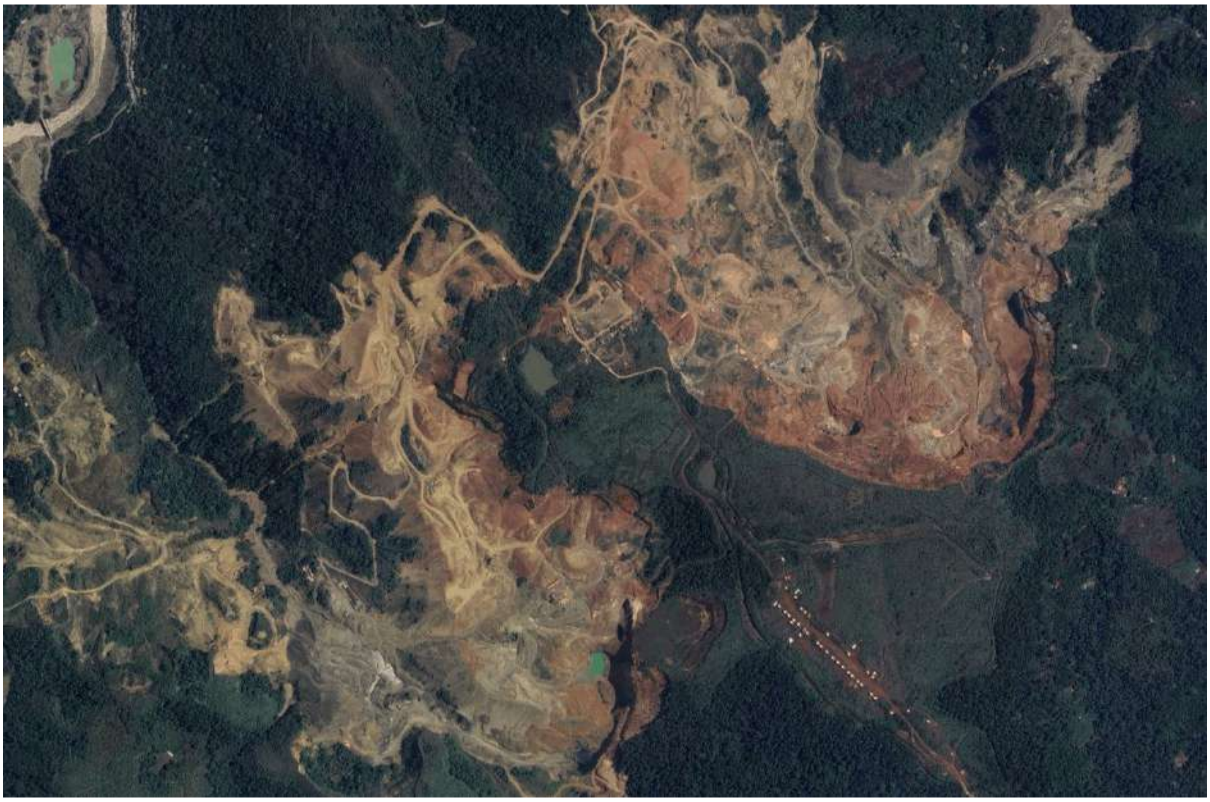
[7] The coordinates for the mine are -12, 09, 25.37.
[8] The coordinates for the mine are -15.88, -67.01.

this paper, we systematically document the features of missing mines. Applying new detection techniques indicates a significant gap in the form of missing mines. Furthermore, the missing mines tend to be relatively small but can be found across a wide array of institutional settings. That said, countries with higher shares of smaller missing mines exhibit lower control of corruption, one of multiple sources of misreporting. A central part of this paper is to explore the implication of the use of new techniques for our understanding of the link between mines and respectively civil conflicts and deforestation.

Figure 1. Wrongly identified mine in the S&P dataset

Figure 2. Zambian Mine identified using satellite imaging but not in the S&P dataset

Figure 3. Peruvian Mine identified using satellite imaging but not in the S&P dataset



The remainder of the paper is organised as follows. Section II compares old versus new techniques for detecting mines. Section III provides an anatomy of missing mines. Section IV discusses the implications of the use of new techniques. Section V concludes.

II. Old versus New Techniques for Detecting Mines

In this section, we compare the old and new techniques for detecting mines. Most academic research currently focused on geospatial mining activities relies on S&P's Capital IQ Pro[9] data for geolocated mining activity. Many studies including the above referenced hinge on a set of assumptions related to a spatial identification strategy. The first assumption is *spatial exactness* (i.e. a mine is located where it is reported to be located). The second is *sample completeness* (i.e. covering all mines in your sample). Despite the salience of the underlying data used in the analysis, very few studies have examined whether these implicit assumptions hold true. In the following, we try to answer basic questions about the properties of the S&P data and how advances in satellite imagining and AI provide new and more efficient detection techniques.

How does S&P Capital IQ Pro collect information? S&P Capital IQ Pro foremost relies heavily on publicly available company data, most of which is based on self-reporting. That includes company reports, disclosures, press releases, company filings, and investor presentations. S&P being a proprietary dataset, it is not open-access and exists behind a paywall, thus limiting wider use. When evaluated at the country level, S&P Capital IQ Pro does generally exhibit significant differences to nationally reported total production amounts and exports. Instead, when evaluated at the more granular level, mining locations often do not exist and are spatially misaligned, or reported locations do not show mining activity. Additionally, S&P and comparable mining datasets, such as a recently published Global Mining database by the International Council on Mining and Metals (ICMM, 2025), report location in point locations, making it impossible to estimate the physical parameters of any mine. Given that mines with vertical and horizontal footprints have very different environmental consequences, information on the physical footprint of mines is an important metric generally fully absent in the standard data sources.

Given the specific visual footprint and rival nature of land use, various satellite based derived information can be used to detect locations of potential mining activity. Previous related work attempted to work mostly on raw imagery bands (Werner and Maus, 2024; Liang et al, 2021).

[9] Formerly also known as SNL's Metals and Mining and Raw Materials Group

Here we use a simpler workflow, leveraging the newly developed range of geospatial foundation models to increase computing efficiency. As outlined above, various challenges exist that have so far substantially limited the accurate measurement of mining activity. However, while illegal and artisanal mining remain prevalent factors, the revolution in technology across the past decades have also opened doors for new approaches to a more transparent and accurate measurement of mining sites.

The substantial increase of high-resolution imagery and innovation in satellite-based optical instruments), paired with the rapid advances in AI and Machine Learning offer substantial pathways to analyse global imagery at scale and speed (Burke et al, 2021). While these advances are much broader than the value they provide in this context, the identification of the location of mining activity offer a suitable case for satellite-based data analytics. Mining activity is characterised by very specific optical footprints. For example, they are often associated with a discontinuous change in forest cover (e.g., Luckeneder et al, 2025), exhibit water bodies such as tailing dams, and cover a large square foot area. All these optical indicators imply a suitability of satellite-based mining detection. Initial studies using earth observation for mining detection started with manual inspection and delineation of mining sites (Werner et al, 2020; Maus et al, 2020), which has more recently been replaced with algorithmic identification of mines on high-resolution satellite imagery (Tang and Werner, 2023).

While recent advances in high-resolution imagery offer vast treasure troves of data, they often come with substantial costs, which not only hinders studies to purchase proprietary data but also limit the further development of such algorithms due to cost limitations. We use recent state-of-the-art geospatial foundation model embeddings[10], foremost Google and Deepmind's AlphaEarth (Brown et al., 2025), in combination with Meta's Segment Anything v3 (Carion et al, 2025) and Dino v3 (Siméoni et al, 2025) models for a streamlined open-access approach. Across the very recent past a new class of model, *geospatial foundation models*, have emerged within the context of earth observation as a new class of models. Models such as Google's and Deepminds AlphaEarth (Brown et al., 2025), IBM's Terra Mind (Jakubik et al, 2025) and the University of Cambridge's Tessera model (Feng et al, 2025).

[10] Geospatial foundation model embeddings are compact, high-dimensional numerical vectors that represent the "semantic essence" of a geographic location. In other words, these embeddings act as a digital fingerprint that encapsulates a place's visual characteristics, human activity, and environmental context into a standardised format for machine learning—rather than storing raw satellite imagery or coordinates alone.

Geospatial Foundation models are large and pretrained deep learning algorithms that combine and compress multi-sensor and multi-temporal satellite information within a self-supervised learning process. From this process as *embeddings*, one obtains pixel values that encode the various input layers into a single value per pixel. While this value has no intuitive meaning by itself, it can be used as an input in supervised machine-learning models or can be used more directly for more classification and spatial clustering exercises, where pixels with similar features exhibit similar embedding values.

In this workflow, we combine information on known mining locations from Open Street Map, polygon outlines obtained in prior academic studies (foremost Maus et al., 2020; Tang and Werner, 2023) and a set of 200 mining locations obtained via S&P Capital, where the latter was manually cross-tested against satellite imagery and delineated via Meta's Segment Anything model. This set of 2,541 mining locations were then used as labelled inputs to train a supervised shallow neural network classification model built on top of AlphaEarth embeddings to identify pixel embeddings that exhibit sufficient similarity to the input data to be labelled as "mining" based on a probability criterion rule. Once locations have been identified, the prior mentioned Segment Anything model is used to segment, or delineate, the boundaries of the mining polygon. For any of the identified polygons, a nearest-neighbour match is then performed to locations stored within the S&P database and the USGS Global Distribution of Selected Mines, Deposits, and Districts of Selected Mines to identify the most likely mineral mines through spatial proximity to known deposits.[11]

III. An Anatomy of Missing Mines

In this section, we provide an anatomy of the global dataset obtained from the use of new techniques to detect mines.[12] We focus on the large gap between old and new data so-called missing mines.

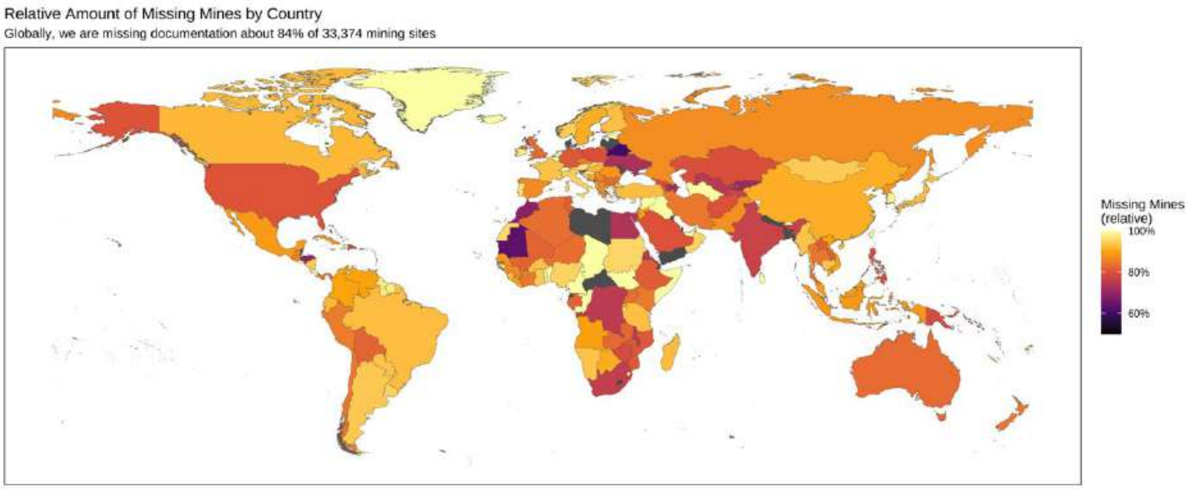
The gap between mines obtained from new and old detection techniques is (very) large. The gap is measured as a share between the gap between the difference between the total number of mines detected with new techniques relative to those detected with new techniques but matched to S&P locations, i.e. those locations that both the geospatial AI workflow detects and S&P

[11] Our "new" methods count mines, not mining output per se. When discussing 'small' vs 'large' this is based on the visual footprint with an assumed correlation between footprint size and output/supply. Further work will aim at eliciting estimates of future output using artificial intelligence.

12 The underlying dataset for this study will be made available via an open-access repository in the near future.

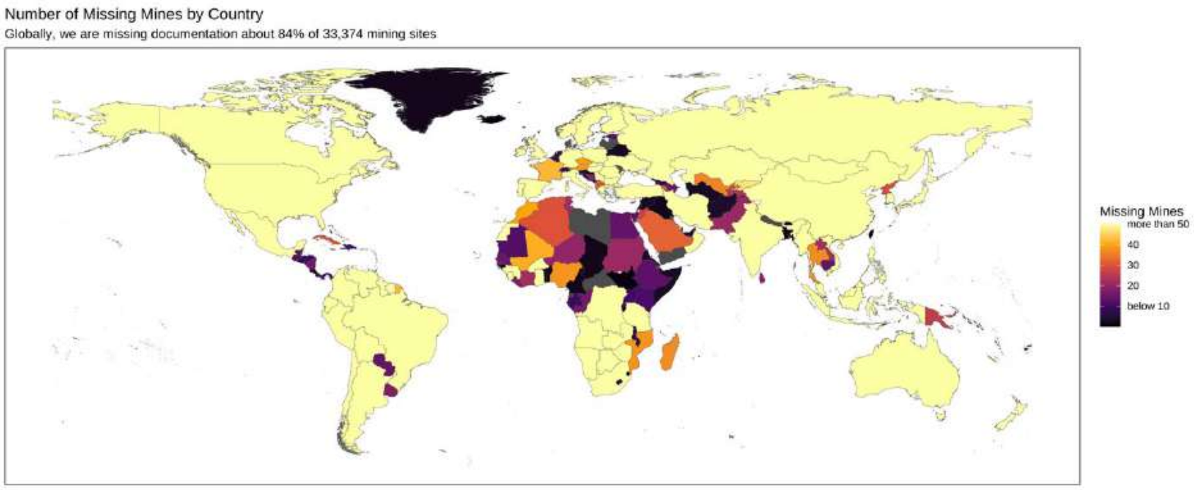
records. Figure 4a shows the mines detected per country that is not accounted for within S&P as a fraction of the total amount of mines detected (including those sites also listed within S&P data); Figure 4b shows the equivalent but in absolute terms, simply as the number of non-recorded mines. It provides a global perspective on missing mines. The prevalence of missing mines is widespread and not confined to one specific region, albeit Africa displays more differences across countries. Mining sites in extremely dry areas such as deserts are generally harder to identity via remote sensing. That can partly explain the lower numbers of missing mines detected across the Sahel countries.

Figure 4a. Global perspective on missing mines



Key: The map shows the missing mines relative to the total of S&P mines and mines detected by new techniques**.**

Figure 4b. Global perspective on missing mines

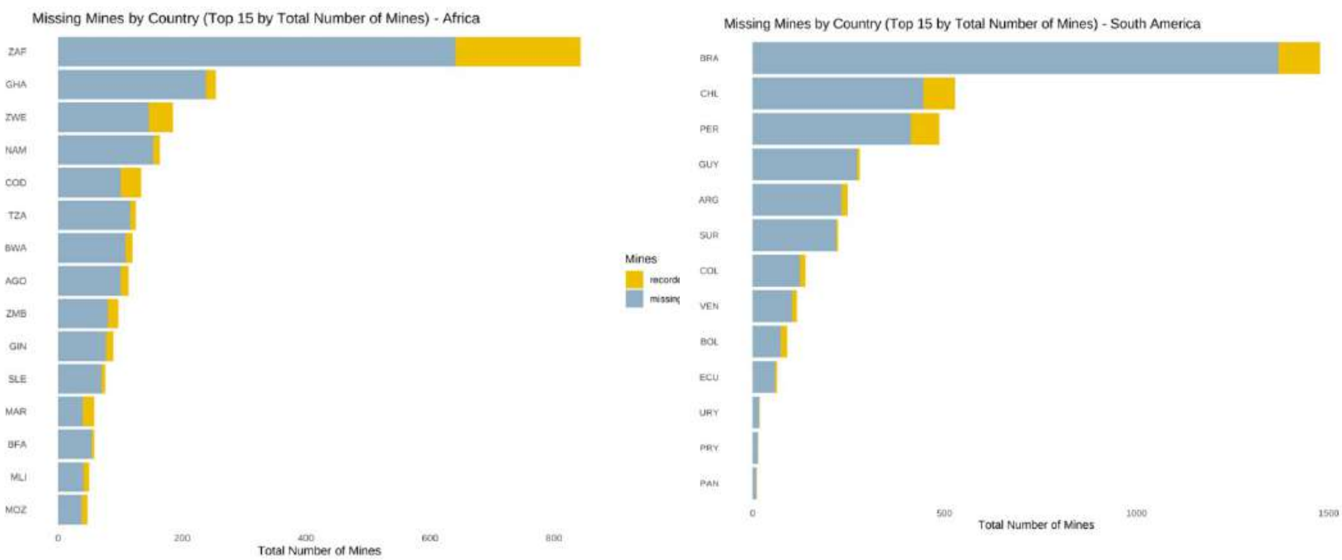


Key: The map shows the absolute number of missing mines per country.

More importantly, S&P records mining locations as points, as opposed to the shape of the mine. Instead, remote sensing geolocates the whole area covered by mines. To account for that crucial difference, mining locations within a 500 meters radius of earth are assumed to belong to a mining site which we subsequently attempt to match to a location recorded within S&P's data catalogue of mining locations. The matching process between the two sources of data could yield false positives. That caveat is inextricable considering the recording by S&P mines merely as points. Notwithstanding, these technicalities that may only explain a small portion of the differences. The number of mines detected with remote sensing is vastly larger than those listed in the S&P database.

Figure 5 provides a regional perspective for sub-Saharan Africa and South America. It shows the number of mines which are a match between those detected by old and new techniques and those only detected by new techniques. Zimbabwe and Brazil stand out as having the largest number of mines for each region. Most mines for these two countries are detected by new techniques but not by old techniques.

Figure 5. Regional perspective on missing mines



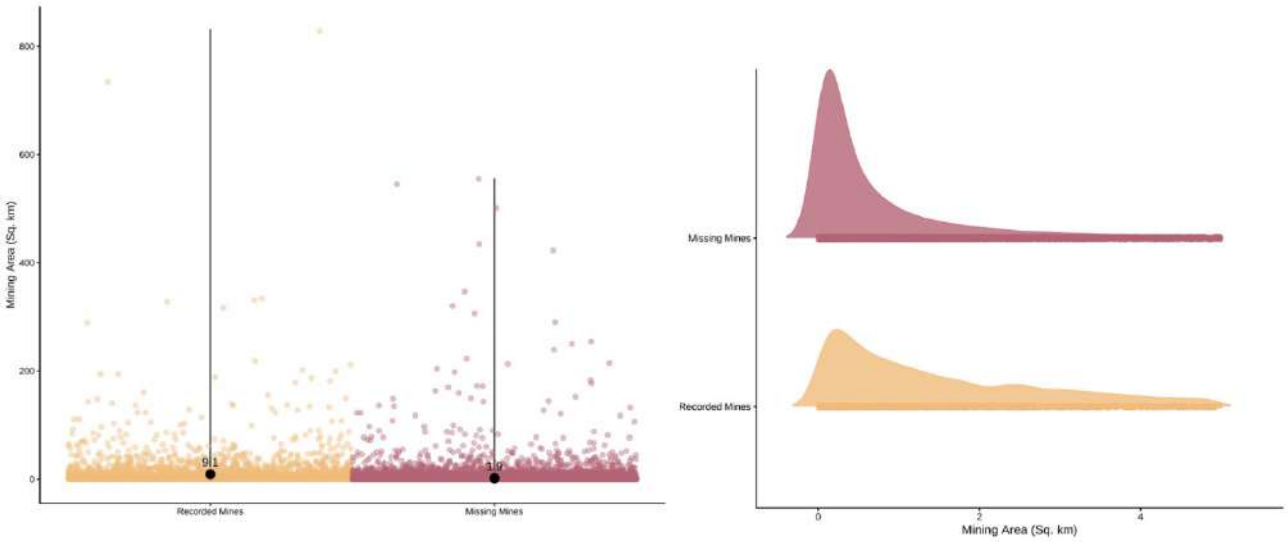
Key: The sum of the bars of each colour indicates the total number of mines detected by country. The yellow mines indicate those locations successfully matched to mining locations listed within S&P, whereas the blue colour indicates mining locations that are not recorded within S&P.

Instead, other countries included in Figure 5 display much smaller number of mines and smaller gaps between those detected by new and old techniques. These results are consistent with the growing evidence that existing datasets substantially underestimate the number of mines around the world. The issue of missing mines is also widespread.

Now that we have documented the wide gap in the data which appears when using more systematic techniques, it is useful to parse the missing mines data. A quick look into the size of missing mines relative to non-missing mines suggests that the former are much smaller. Indeed, on average missing mines are 1.9 square kilometres, while non-missing mines are on average 9.1 square kilometres.[13] Figure 6 illustrates the distribution of the size of recorded and mining sites for all sizes (left) and zooming in on mines with a size of less than 5 square kilometres (right). The distribution of non-missing mines is much wider with exceptionally large ones driving up the average. These basic facts support the notion that missing mines are largely the results of ASM. Indeed, the latter are a growing feature of global mining activity. Further, we correlate missing mines with indicators of the quality of institutions at the country level. Figures A1-A5 in the Appendix show correlations between missing mines with country-wide indicators of respectively rule of law, government effectiveness, control of corruption, voice and accountability and political stability and absence of violence. Across the board, Figures show that missing mines are prevalent across countries with a wide difference in the quality of institutions. These results suggest that missing mines are not driven by specific elements of institutions. That said, countries with higher shares of smaller missing mines exhibit lower control of corruption. That is, consistent with corruption, there is a source of misreporting coupled with the presence of artisanal mining.

[13] Calculations exclude the mines that exhibit outliers in their physical size--one of them is classified as missing, two are recorded mines. Including these outliers would change the average physical extent of missing mines to 2 square kilometres for missing mines, and 17.1 for recorded mines.

Figure 6. The relative size of missing mines



IV. New techniques for Detecting Mines, Conflict, and Deforestation

In this section, we explore some implications of the use of new techniques to detect mines. The nature and extent of the gap may have radical consequences on our understanding of global mining and its consequences. The comprehensive nature of the database presented in this paper is helpful to revisit environmental, social and developmental spillovers stemming from the growing number of mines linked to critical minerals.

Generally, the dynamics of global and domestic mining output and depletion rates could be grossly mismeasured when using old detection techniques. These could create important inconsistencies with trade statistics and domestic tax revenues. On the environmental and social front, existing studies evaluating the effect of mining on deforestation and conflicts may need to be revisited. Predicting environmental damage and conflict as well as designing policy interventions could be vastly enhanced by using more comprehensive coverage of mines.

More specifically, illegal and artisanal mining activity further increase issues around reliable and transparent data. A substantial number of mines are also not reported in the S&P dataset. Missing mines create a substantial underreporting of mining activity. This leads to substantial measurement biases in subsequent analyses where estimated elasticities with respect to any further covariate should be consumed with caution. Displaced mines, i.e. mining locations are not accurately indicated but are indicated somewhere in the vicinity. This creates issues for all work using spatial distance as an identifier (e.g., in mine-conflict studies as in Berman et al, 2017). Wrongly indicated mining locations where no mining activity exists. Mining locations are reported as point features (longitude/latitude). This limits the understanding of the actual physical footprint and extent of mining activity (see also Maus and Werner, 2024).[14]

IV.1. Mining and conflict

Hitherto undetected mines may correlate with unreported armed group financing, border-region violence, and illegal taxation networks. New techniques to detect mines may reveal far more mining activity in buffer zones, protected areas, and frontier regions than assumed.

The question of whether mining can be linked to conflict patterns has gathered substantial attention over the years (Berman et al, 2017). However, matching mining sites spatially to conflict locations only allows for an identification of the connection between the two variables if both are measured in completeness and in spatial accuracy. We show that the latter suffer from substantial measurement issues. To assess whether the measurement issues of the mining sector affect our current understanding of how mining activity relates conflicts, we employ geospatially tagged conflict data from the Armed Conflict Location & Event Data Project (ACLED), the most often used conflict data source in this context across the literature. We match each detected mining site to conflicts within a 100km radius of the mine across all Sub-Saharan African countries[15].

We apply the same method to locations listed in the S&P dataset to detect the number of conflicts within this 100 km radius. Figure 7 shows the results for those countries where we could detect conflicts within mining site proximity across Sub-Saharan Africa. Overall, substantially more conflicts could be matched to mining sites if we use satellite-based mining locations rather than solely those listed within the S&P dataset. Assessing differences across countries, heterogeneity exists, where most countries exhibit the same pattern that holds overall, but where some countries show slightly divergent patterns.

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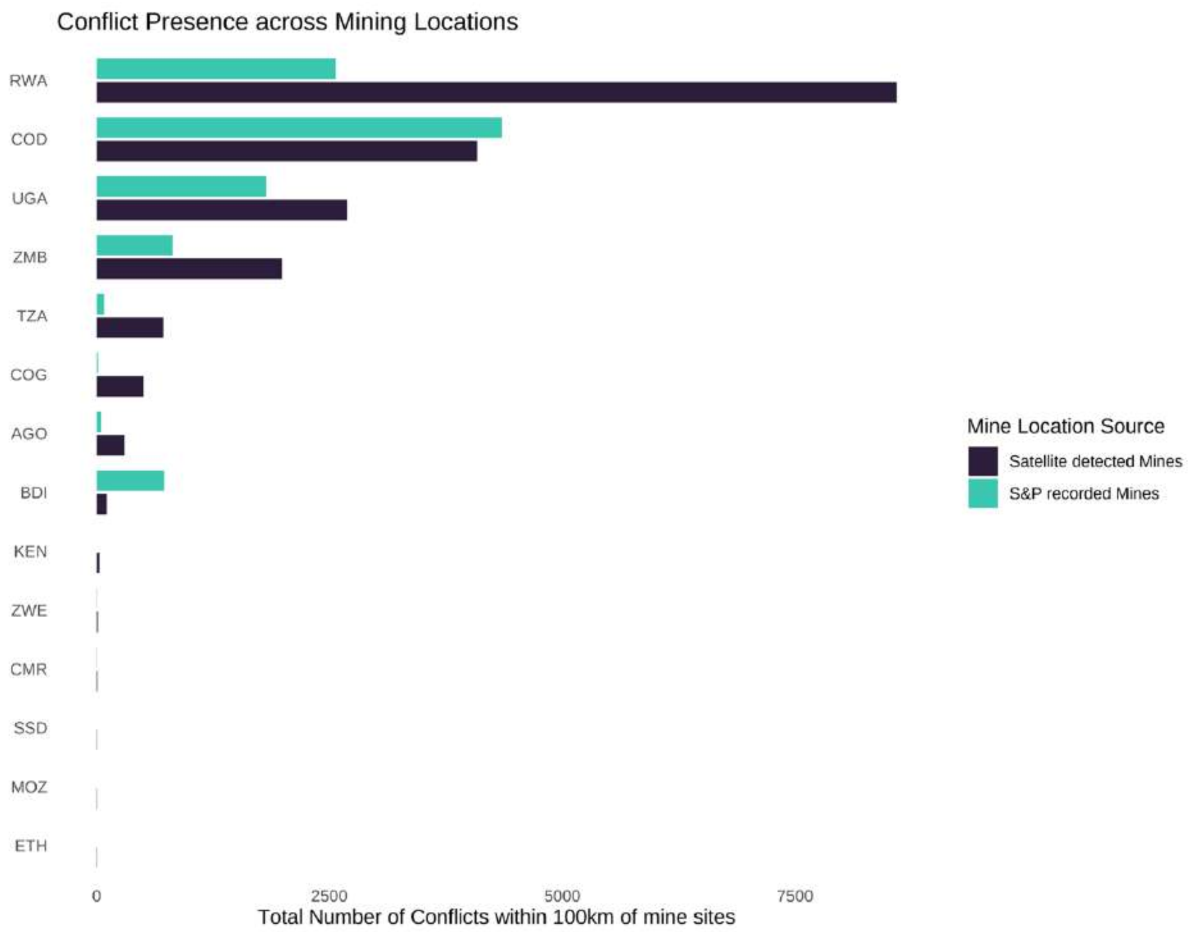
[14] Illustration Dashboard: https://samirabarzin.users.earthengine.app/view/mining-illustration

[15] S&P and satellite data underlying this analyses stem from the year 2022, thus conflict location data has also been limited to represent conflicts across 2022.

Figure 7. The Number of Conflicts in Proximity to Mining Sites



The Democratic Republic of the Congo (DRC) records slightly more conflicts in mining proximity when S&P locations are used than when satellite detected locations are used. This might be driven by the fact that S&P locations exhibit spatial clusters in the DRC where conflicts are matched to multiples mines, whereas satellite-based metrics might show more spatial dispersion and thus curb this double accounting of conflicts within mining proximity leading to a slightly lower total. Another outlier is Burundi, where results are driven by two mining sites listed in the S&P dataset but that are not detected by satellites that close to the border with the DRC. A match of mines to conflict sites in this case thus captures conflicts in proximity to these sites but located in the DRC; those conflicts are not located in proximity to those mines detected for Burundi by the satellite workflow, therefore reducing the count of conflicts in proximity to satellite detected mines. For one of these two Burundian mines, a visual of the given location is provided in Figure A.6 in the Appendix.

Overall, these results suggest that our current understanding of the relationship between conflict and mining activity is affected by measurement issues existing in the mining sector. It is thus paramount to reassess the empirical results in the literature on mining and conflict with our new data employing state-of-the-art techniques.

IV.2. **Mining and corruption**

The literature on the resource curse has documented extensively the link between resource windfalls and corruption at the country level (see for instance Arezki and Brueckner, 2011; van der Ploeg 2011; Ross, 2001) and at the local level (see for instance Knutsen et al, 2017). In the context of undetected and undeclared mining activity, it cannot be assumed that assessing the linkages between corruption and mining activity is representative across both recorded and unrecorded mining sites. This will hold especially given that undetected mines are on average structurally different to those recorded. The latter tend to be industrial mines under corporate structures and those not recorded tend to consist of artisanal and small mines and illegal activities.

Arguably, the causality between corruption and mining activity can run both ways and we are not here attempting to focus on a specific direction but rather explore the association. Specifically, we are opening the discussion on how the link between corruption and mining activity might differ when one assesses only those recorded mines versus all mines (i.e. those detected via satellites and those officially recorded). We thus present a simple correlation analysis to test for differences. For the corruption data, we rely on geolocated information of the Afrobarometer project on perceived corruption.[16] We merge the Afrobarometer information on perceived corruption at the boundaries of admin 1 region and rely on the weighting factors reported to create a weighted perceived corruption variable at the admin 1 level. Subsequently, we merge this with the number of reported and detected, but not reported mines at the same spatial boundary, and test for heterogeneity in correlation.

Figure 8 presents the results. The negative correlation presented across both plots reiterates that mining resources tend to exist in places where corruption is higher.[17] However, the perception of corruption tends to be associated more strongly with mining activity of official mines, and somewhat less pronounced when assessing the correlation of corruption to both officially recorded and unrecorded mines. These results could, however, be indicative that there exists

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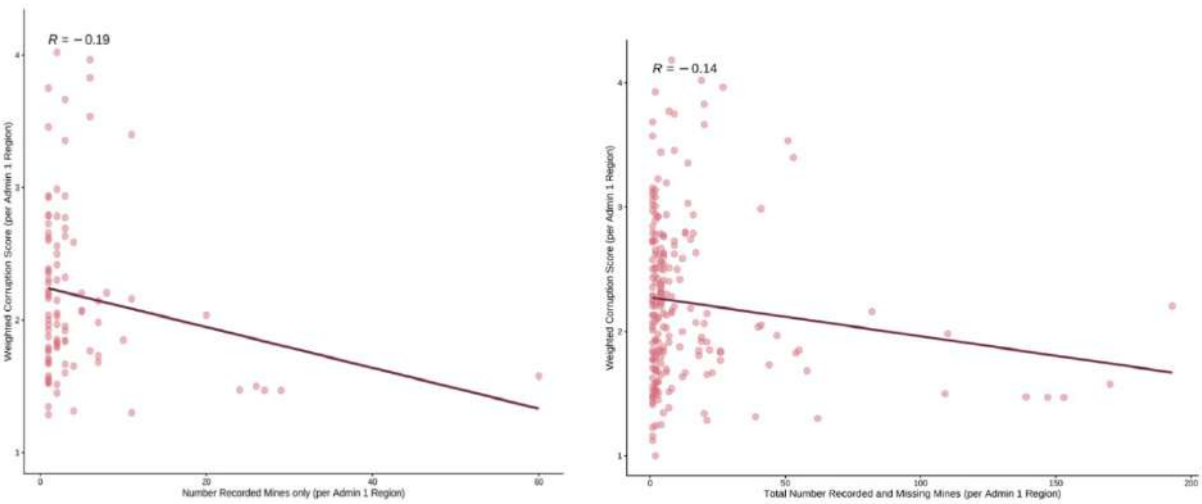
[16] Afrobarometer data covers solely the African continent, hence the results of this section relate to Africa only.
[17] Given that Afrobarometer codes increases in corruption with lower numeric attributes than decreases in corruption, where the variables range from 1 for large increases to 5 for substantial decreases,

structurally more corruption within recorded mines, which would generally imply relatively higher degrees of corruption in industrial mining activity as compared to artisanal and small mines or simply informal mining. Another hypothesis is that considering the data being about perception, respondents might hesitate to make statements of corruption in locations with high degrees of undetected mining activity, which potentially implies higher degrees of illegality and informality. These initial insights, however, suggest that relying solely on recorded mining activity to investigate corruption in the context of mining is only revealing parts of the story.

Figure 8. Mining and Regional Corruption



IV.3. Mining and deforestation

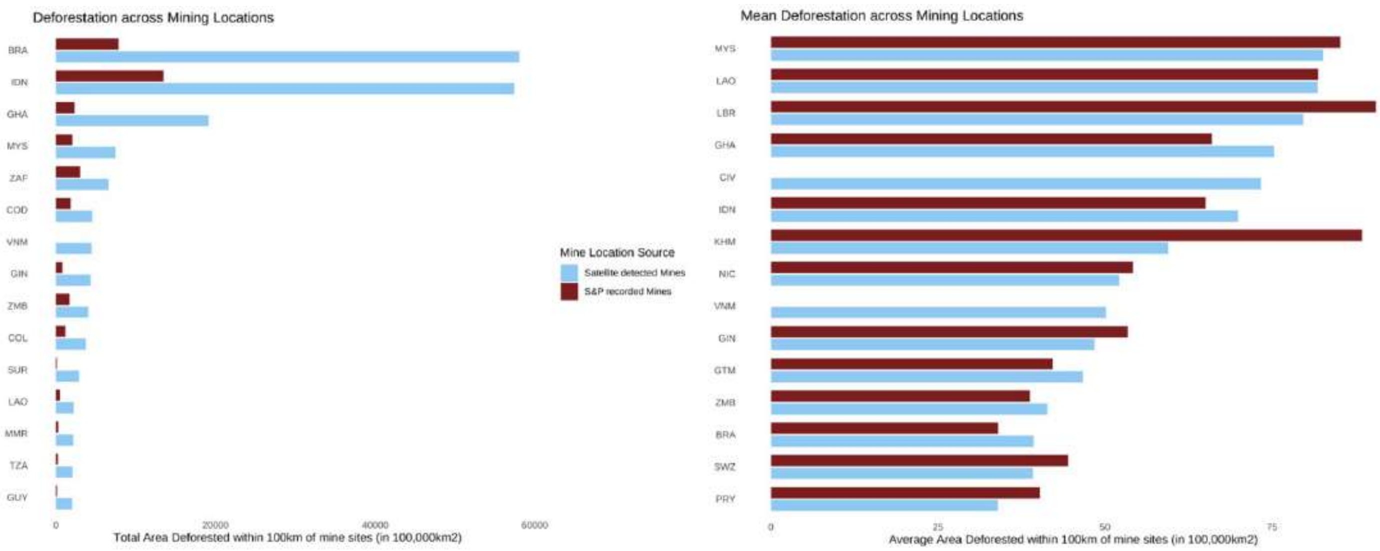
Another strand of literature that receives significant attention is the study of the environmental impacts of mining on surrounding areas, including both intensive margin elements as water pollution (Vashold et al, 2026s) or extensive margin elements as the effects of mining on land use changes (Maus et al, 2022). However, given the measurement issues prevalent in officially recorded information, we revisit the validity of these results on the environmental impacts of mining by using the set of mines detected via our satellite-based detection algorithm. While the re-assessment of all potential environmental impacts is beyond this paper, we initiate here the re-assessment of these issues by estimating the approximate area of forest cover lost due to mining operations. We select the set of mines, both those recorded within S&P set and those identified via our satellite-based workflow, that fall within the regional areas of Latin America, Sub-Saharan Africa and South-East Asia, which are the regions with the most prevalent deforestation patterns. For each mine of either set, we calculate the total area of deforested land (or change in forest cover from forested to non-forested) between 2000 and 2024 within a 100 square kilometre radius of each mining site where we rely on the deforestation data layers stemming from Hansen et al (2013)[18]. Results of the total and per mine average area of land deforested within 100km proximity to mining sites by country are shown in Figure 9 for the top 15 countries of deforested land in the vicinity of satellite based mine site detection.

Unsurprising, the total area of deforested land surrounding mining sites is of magnitudes higher when using the layer of mining sites obtained via satellite vs. officially recorded mines. This clear result is foremost driven by the fact that the quantity of mines is substantially larger in the satellite-based mining location layer than in the benchmark data of S&P. Furthermore, and additionally in line with the literature, we find that the largest degrees of deforested land can be found in the Brazil and Indonesia by far. While mining related deforestation is undoubtedly a contributing factor, other factors influencing the large deforestation trends here are also contributing elements. While a causal study of these effects here is beyond the scope of this paper, the main conclusion of an underassessment of deforestation patterns when using only officially recorded mining locations stands clearly.

In addition, we assess the average area of deforested land surrounding mining locations by country. The differences we find in this assessment are substantially less stark across satellite-based mining detection and for those mining locations recorded via S&P as those discussed prior relating to the total area of deforested land. The main conclusion we draw from this stems from the substantially smaller average size of mines detected via satellite, where given the much smaller physical footprint of the mine and often associated remoteness or informality, large scale infrastructure is not expected to follow these mining operations. Hence, larger mines will on average be associated with further infrastructure and wider land use changes (through attracting labour force which in turn generally implies land use changes in terms of built-up area and agriculture), whereas smaller mines are not. Additionally, we observe another set of countries as the most prevalent exhibiting these patterns as compared of the total areas deforested, where it can be deduced that for countries such as Myanmar and Laos that exhibit the highest patterns, small mines comes with relatively starker land use changes than they come in those places that exhibit large total deforestation but relatively smaller average deforestation patterns, such as Brazil and Indonesia.

[18] Data processing has been conducted on Google's Earth Engine platform

Figure 9. Deforestation across Mining Sites



In conclusion, we draw two important insights from this discussion: (1) the total amount of deforested areas in the vicinity of mining operations is largely underestimated when relying solely on officially recorded mining sites, and (2) mines that do not appear in officially recorded datasets tend to exhibit similar average deforestation patterns, but given the larger number, the deforestation linkage to not recorded mines is expected to be smaller due to the smaller physical footprint of these mines and the lack of complementarity of these mines to infrastructure developments.

V. Conclusion

Global mining activity is dramatically mismeasured. Traditional datasets undercount artisanal, illegal, informal, and expanding operations, leading to fragmented and incomplete assessments of global mining activities. New techniques combining satellite imaging combined with AI offer a far more efficient and comprehensive record of global mining activity. Evidence suggests that traditional datasets miss out including on the growing ASM activity. The issue of missing mines is prevalent across a wide array of institutional quality. Employing new techniques yields important implications on our current understanding of the effect of mining on deforestation, conflicts and economic development.

Linking back to the surging interest for critical minerals including from global superpowers, the identification of mines, in a much more comprehensive manner than before, is an important step forward. The methods presented in this paper can be used to provide a visual footprint to say what kind of mines we are identifying. That would help with determining the extent to which the minerals will be integrated in supply chains, what possibility there is to do local processing, and how "appropriable" the mineral is (e.g., gold vs. lithium). That will help determine the extent of the value chain that can be created and the potential for conflict. Overall, the availability of this will increase transparency at the time of the surge of interest for critical minerals. All actors involved, both private and public, will have to take account of that increase level of scrutiny. Local communities and the citizenry at large will be empowered to demand more accountability and reap the benefits.

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APPENDIX

Figure A1. Missing Mines and the Rule of Law

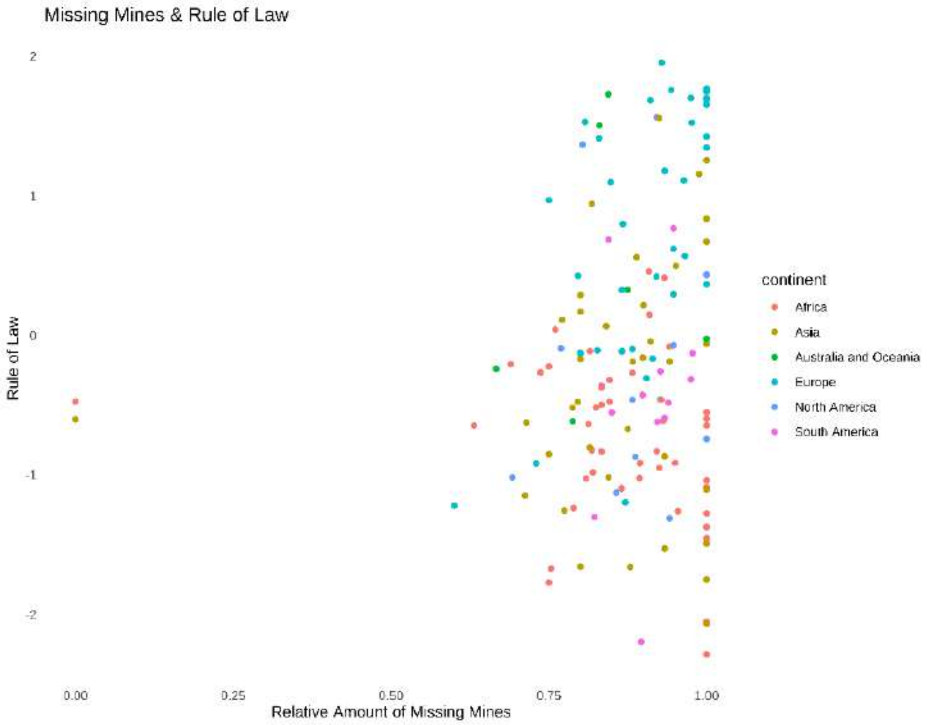

Figure A2. Missing Mines and Government Effectiveness

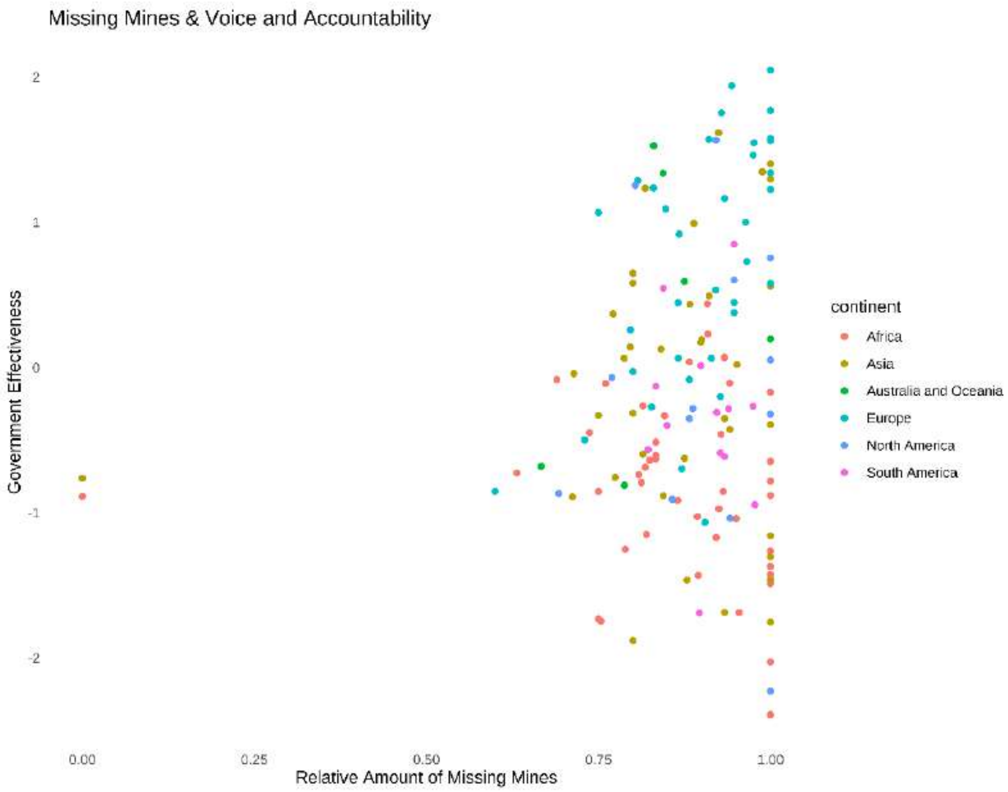

Figure A3. Missing Mines and Control of Corruption

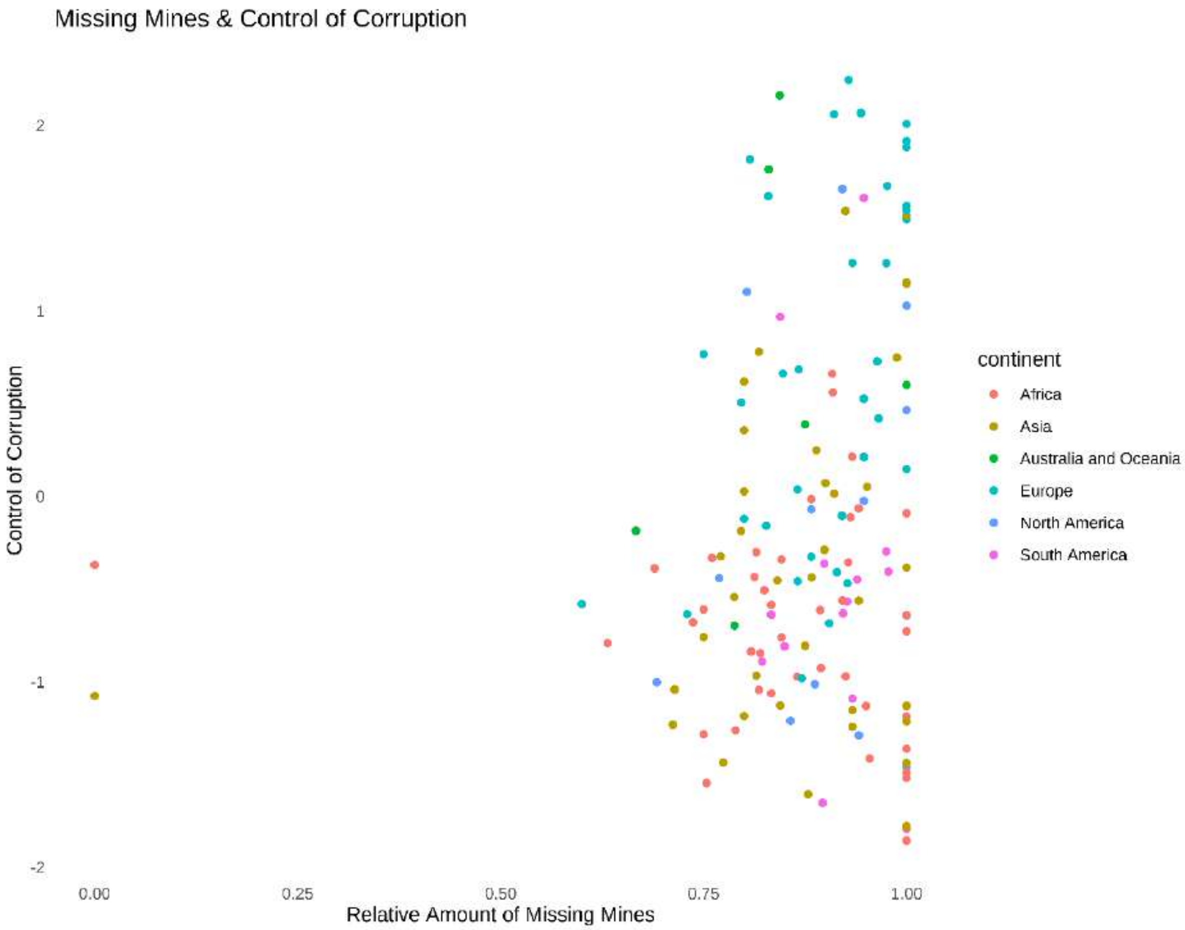

Figure A4. Missing Mines and Voice and Accountability

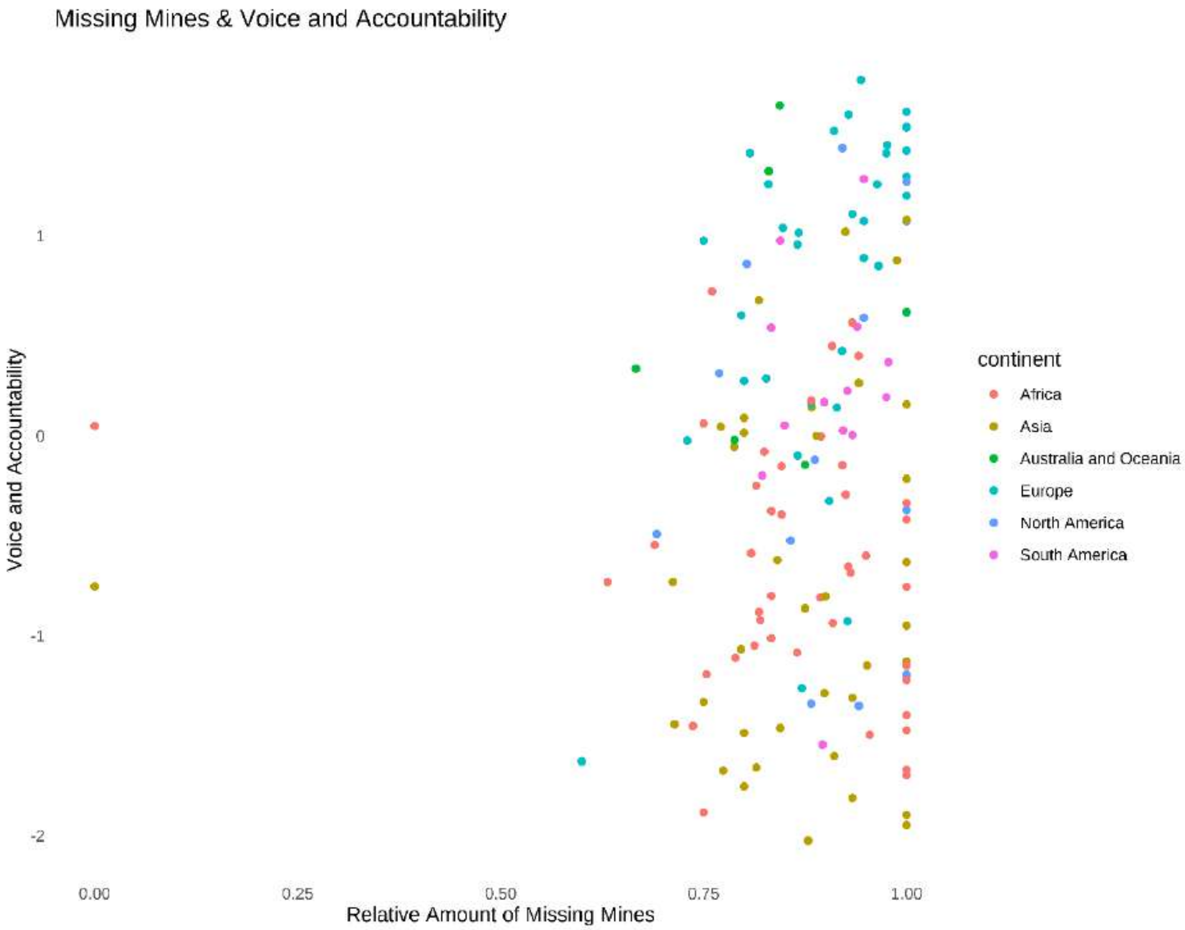

Figure A5. Missing Mines and Political Stability and Absence of Violence

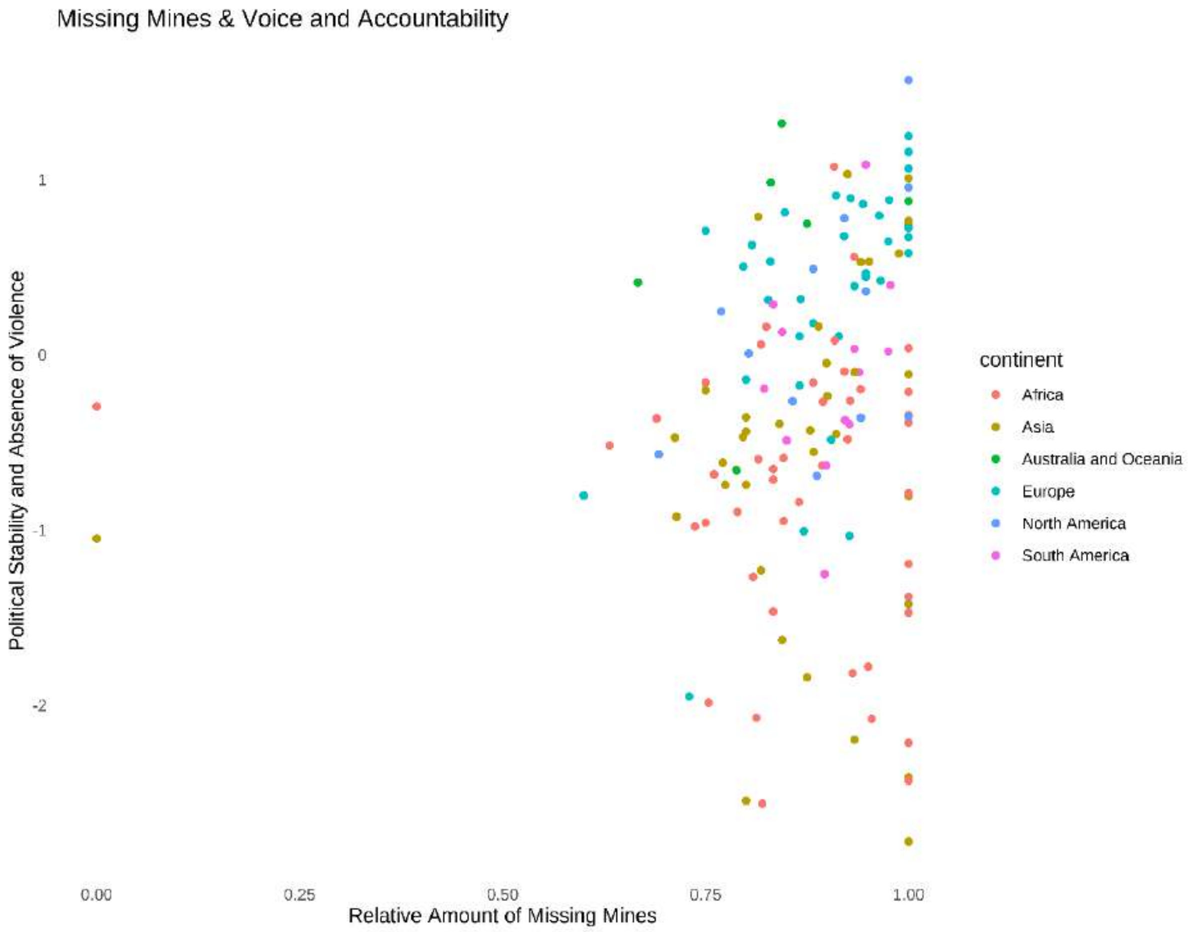

Figure A6. Burundian Mines close to the border with the DRC listed in the S&P dataset

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