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Life cycle inventory data for critical mineral mining: recommendations and new U.S. data compendium

Jenna N. Trost,[a] Daniel Zitomer,[b] Natalia Gutiérrez Rodríguez[a] and Jennifer B. Dunn *[ac]

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Production and pollution data and information for United States critical mineral mines are heavily fragmented across numerous databases and sources, such as government emissions reports and company documents. These disintegrated data complicate fair and consistent analyses and communities' understanding of mine operations and impacts. For 19 active critical mineral mines in the United States, we aggregated location, production, and emissions data and developed an interactive data compendium map and data set. We calculated the ecotoxicity, human health cancer, and human health non-cancer life-cycle impacts of the emissions from these mines. Further, we analyzed the proximity of these mines to disadvantaged community tracts identified by the Justice40 initiative and found all mines are within 29 miles of a disadvantaged tract. We defined a methodology to develop probability distribution functions for mining pollution data to support robust mining life cycle inventory data. Finally, we discussed next steps to expand the data compendium to additional critical minerals and other countries like Australia and Chile. Reducing fragmentation in mine emissions data is important because aggregated or old data masks unique features of individual mines including geology, hydrology, and geography. Furthermore, given changes in time in ore grade and mining technology, recent data best capture the contemporary impacts of an individual mine.

Environmental significance

Mining is the foundation of the critical mineral supply chain that feeds into the manufacturing of lithium-ion batteries. Mineral demand is surging and understanding, quantifying, and mitigating the environmental effects of mining is essential. Life cycle assessment (LCA) is a key tool in this process, but a major challenge remains: the lack of reliable data to support comprehensive critical mineral mining LCAs. Commonly used data sources for mining LCA are often outdated and not geographically representative. Generating recent, geographically-representative data is challenging, however, because data are often fragmented across multiple sources. To address these gaps, we have launched a data compendium for copper, lithium, and nickel critical mineral mines in the U.S. to provide essential data for more accurate LCAs. We also provide guidance on how to address uncertainty in mining pollutant emissions data for use in LCAs.

Introduction

The energy transition, which aims to advance cleaner and less carbon-intensive energy sources than conventional fossil fuels, involves scale up of many minerals-dependent technologies including lithium-ion batteries, solar panels, and wind turbines. Many of these decarbonization technologies use critical minerals,[1] like copper, lithium, cobalt, and nickel. Life cycle assessments (LCA) that conclude these technologies reduce fossil fuel consumption and greenhouse gas (GHG) emissions have generally served to justify the environmental benefits of these decarbonization technologies.[2,3] LCAs are holistic analyses that account for the environmental effects of every stage of a product's life cycle. Producing insightful LCA results requires robust and reliable life cycle inventory data that quantifies energy and material flows, including emissions to air, water, and land, for each life cycle stage.[4,5] LCAs of minerals-dependent technology, however, often lack high quality data for the minerals mining stage.[6]

Data quality is a key consideration in LCA. Weidema (1998)[7] proposed a data quality matrix to guide data choices for life cycle inventories that includes five indicators. The first indicator assesses the reliability of the source. The most reliable data is based on measurements whereas the most complete data is generated from numerous sites over a period substantial enough to even out typical fluctuations. In the context of mining, high quality emissions data should therefore be measured at multiple mining sites over a period that would capture variations in emissions that arise from normal process variations. Per Weidema,[7] high-quality data should also be less than three years old, from the region of study, and should be from the same type of

[a]Department of Chemical and Biological Engineering, Northwestern University, Evanston, IL, 60208, USA. E-mail: jenniferdunn1@northwestern.edu
[b]Department of Earth, Environmental, and Planetary Sciences, Northwestern University, Evanston, IL, 60208, USA
[c]Center for Engineering Sustainability and Resilience, Northwestern University, Evanston, IL, 60208, USA

industrial processes that the LCA aims to capture. Obtaining high-quality data for minerals mines is challenging but important.[8,9] Notably, environmental impacts of mines can depend greatly on location because of several factors: the stringency of local environmental regulations, choice of technology and management practices within a mining operation, ore grade, and others. Furthermore, mining technology is evolving to reduce water and energy consumption.[10–12]

Critical mineral LCI data in LCA models and databases

In existing peer-reviewed literature, the quality and sources of data used to conduct critical mineral mining LCAs varies. Yet, no open-source database with contemporary, location-specific environmental impact data from critical minerals mining exists to improve the underlying quality of life cycle inventory data that underpins LCAs. Based on our recent literature review,[6] under half (40%) of critical mineral mining LCAs use primary data from mines. Primary data are essential for developing accurate LCAs that best reflect an individual mine and its localized impacts. Others use common databases like Ecoinvent (37%) and the Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET) model[13] (1%) while many draw LCA parameters from the literature (19%). Given the prominence of Ecoinvent as a data source, understanding the provenance of data for minerals in this database is essential for determining the quality of these LCA results. We examined several examples in Ecoinvent to consider strengths and weaknesses of mining life cycle inventory (LCI) data it contains. One example is the reference product "copper mine operation and beneficiation, sulfide ore." This product's data includes nine country-specific datasets and one dataset representative of rest-of-world (RoW). The nine countries with specific datasets are: Australia, Canada, Chile, China, Indonesia, Kazakhstan, Russia, United States, and Zambia. These datasets do not include material and energy flows or pollutant emissions from individual mines. LCI data at the country-level is generated by scaling LCI data of beneficiation reagents (*e.g.*, lime and sodium cyanide), electricity, and water consumption from Classen *et al.* (2009)[14] based on the country's average ore grade, a method outlined by Northey *et al.*[15] Copper concentrate refining data are based on pyrometallurgical copper production and anode sliming.[16] However, pyrometallurgical processing only accounts for about 80% of copper production.[17] The remaining 20% is from hydrometallurgical processing.[17] While Ecoinvent states that these datasets are temporally, geographically, and technologically representative, two of the datasets are more than 10 years old, geographical representation is derived from a national-average average ore-grade, not a specific mine ore grade, and the data may not be representative for mines that undergo hydrometallurgical processing. Notably, most of the underlying data sources in Classen *et al.*[14] are from sources that are years older (*e.g.*, Krauß *et al.* (1999)[18] and Ayres *et al.* (2002)[19]). Given that Ecoinvent's home is Switzerland, the background data often includes data from European or Swiss sources, even for processes that occur outside of Europe. For example, the production of copper concentrate from sulfide dataset that is labeled as geographically representative for Australia uses chemical agent data from Switzerland or Europe. This mismatch is present for the other eight countries, too.

Ecoinvent's data for "cobalt production" is another dataset with low temporal and spatial representativeness. Eight major cobalt producers were surveyed in 2012 to collect primary, site-specific data to build the inventory and document emissions. Ecoinvent users must use this global average data set. It is not possible to refine cobalt LCI data based on location of mine, technology in use at mine, or other factors. Because these producers and their locations were not disclosed, it is difficult to understand data provenance and to be confident in the global representativeness of the data set. Global representativeness may not be as relevant for cobalt as it is for copper given that one country dominates cobalt production. In 2012, the Democratic Republic of Congo (DRC) accounted for just over 53% (ref. 20) of global production. In 2024, the DRC produced over 75% (ref. 21) of cobalt globally. The global average dataset for cobalt production in Ecoinvent has a system boundary from cradle-to-gate and encompasses mining, beneficiation (*i.e.*, production of concentrate and/or raffinate solution), primary extraction and further concentration of cobalt, and refining into cobalt metals. The dataset details that its emissions were obtained directly from the sites. Additionally, the "cobalt production" documentation page lists the representativeness at 30%, but does not define how this value was determined. For comparison, the representativeness for "copper mine operation and beneficiation, sulfide ore" is 80% RoW and 95% for each specific country. Again, Ecoinvent documentation does not disclose the method used to calculate these values. Importantly, Ecoinvent does evaluate the quality of values in its LCI by scoring from its data quality pedigree based on Weidema.[7] Ecoinvent also provides the uncertainty distribution and squared geometric standard deviation (GSD2) for its LCI data.[7] This transparency around underlying data quality and uncertainty can help users evaluate the relevance and utility of a dataset.

Another option for obtaining critical mineral mining LCI data is to use the GREET model,[13] an open-source, large LCA model that emphasizes the United States. LCI data for minerals in GREET do address international aspects of the supply chain to some extent. For example, the model contains data for lithium carbonate production in Chile. Nickel LCI data vary with ore grade, but the share of energy provided from electricity *versus* diesel is fixed regardless of level of energy consumption. The electricity energy and emission factors are based on the global production-weighted average for nickel. No mine-specific data are included in the model. A thorough review of technical reports and publications that document data sources in the model can be required to fully understand data provenance in this model. GREET documentation has not adopted the Weidema[7] framework for documenting data quality, so users who aim to use that framework to characterize data quality must do that independently if they choose.

Our review of these two models indicates that analysts seeking to use them may be generating LCA results with relatively low-quality data for the minerals supply chain. In a time of increasing importance of minerals in addressing challenges in decarbonization, communications, and defense technologies, among others, these data quality challenges are pressing. However, to acquire site-specific, recent LCI data for mines is time-consuming. For data to be publicly available, either industry must voluntarily provide these data or must be required to report them to government agencies that then place these data in the public domain. When documentation of the environmental effects of critical mineral mines does exist, it is often decentralized and fragmented. Data from different companies or agencies frequently exist in many locations, in multiple databases, and in different forms (*i.e.*, hard-copy or electronic). For example, the U.S. maintains numerous databases and source of information about domestic mines, but these resources are isolated and not centralized. Plus, some data are confidential, proprietary, or require a subscription to access.

The need for an open-source data compendium

We argue that there is an urgent need for recent, open-source, location-specific life cycle inventory data for mines, including for the U.S. Data needs for U.S. mining historically have not been a priority because the U.S. has not been a major participant in the minerals supply chain. There is a large push, however, for the U.S. to onshore the critical mineral supply chains for energy and material resilience and independence from other countries. For example, an executive order[22] from March 2025 called for expediting critical mineral mining permitting processes and for prioritizing mineral production and processing on federal lands. U.S. mining LCI data is therefore increasingly important.

In response to this urgent need, we have established a data compendium for critical mineral mines. The compendium, in the form of an interactive map and downloadable data, currently contains centralized location, production rate, and emissions data for active U.S. copper, nickel, and lithium mines. In a first-of-a-kind analysis, we use the data gathered in the compendium to compare environmental impacts across mines in the U.S., assessing the importance of temporal and spatial aspects of life cycle inventory data quality. In our recent literature review, which reaches back to 2009, no critical mineral mining LCA explored how the age of data influenced results and most do not address emissions aside from GHG emissions because of data gaps.[6] The compendium we created can help fill these gaps. The compendium can be updated with new data for the U.S., expanded to include additional minerals, and expanded to include data from other countries.

To the best of our knowledge, this data compendium is the only free and publicly available resource that can enable LCAs of critical mineral mines in the U.S. that use recent and local emissions data. These LCAs can in turn permit comparison of mines' environmental performance, which can stimulate informed policies to promote sustainable mineral supply chains domestically and abroad.

Methods

We began with selecting minerals for inclusion. We wanted to emphasize minerals that are central to decarbonization technologies and are considered to have supply chain risks or be classified as "critical." For our data compendium, we investigated mines of critical minerals used in electric vehicle batteries and defined as "critical" by the USGS[23] or the DOE.[24] These criteria limited our scope to copper, lithium, and nickel and the active mines who produce these elements in their primary products. Graphite, cobalt, and manganese are also important critical mineral components of electric vehicle (EV) batteries, but there are no active mines for these minerals in the U.S.[25] Active mines are the those in production as of June 2025.

We relied on the Mineral Resources Online Spatial Data from the USGS and the Mine Data Retrieval System from the Mine Health and Safety Administration (MHSA) for locations and status of mines. Environmental emission data were pulled from the Toxic Releases Inventory (TRI) and the National Emissions Inventory (NEI) from the Environmental Protection Agency (EPA). The data in the TRI are facility self-reported annually and capture land, water, and air emissions.[26] The NEI data, gathered every three years, are primarily collected by state, local, and tribal agencies rather than facilities and these data only represent air emissions of criteria air pollutants (CAPs) and greenhouse gas emissions (GHGs) and optionally, hazardous air pollutants (HAPs).[26] Some overlap exists in the air emissions data for HAPs, but the TRI includes other toxic air chemicals beyond HAPs. Production data were extracted from publicly available permitting documents and technical reports from individual mines. All data and databases used to construct the data compendium are free and publicly available.

We also calculated some of the impacts of critical mineral mining emissions in the US as life cycle analysis impact categories (IC). We translated the TRI and NEI emissions to the LCIA ICs of ecotoxicity (EC), human health-cancer (HHC), and human health-noncancer (HHNC) ICs using the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI).[27] TRACI is an environmental impact assessment tool which provides characterization factors for chemical emissions to air, water, and land in urban and rural environments. We standardized LCIA results per ton of mineral equivalent (*i.e.* payable or embedded mineral amount in a product) per year. Section S1 details the methodology for LCIA calculations. Calculating these ICs provides a lens into localized impacts of critical mineral mines in the US and can help estimate increased impacts with increased mining. Fig. 1 represents a schematic of data sources used to document mine production, emissions, and impacts.

Additionally, we overlaid environmental justice (EJ) indicators onto the mines to probe the spatial relationship between mineral extraction and disadvantaged communities. We used EJ data from the Climate and Economic Justice Screen Tool,[28] which highlights communities that are environmentally and/or economically disadvantaged.

Results and discussion

All data were compiled into a single database and visualized in an interactive map (see Fig. 2).[29] The database excludes proposed and closed mines as neither are actively producing

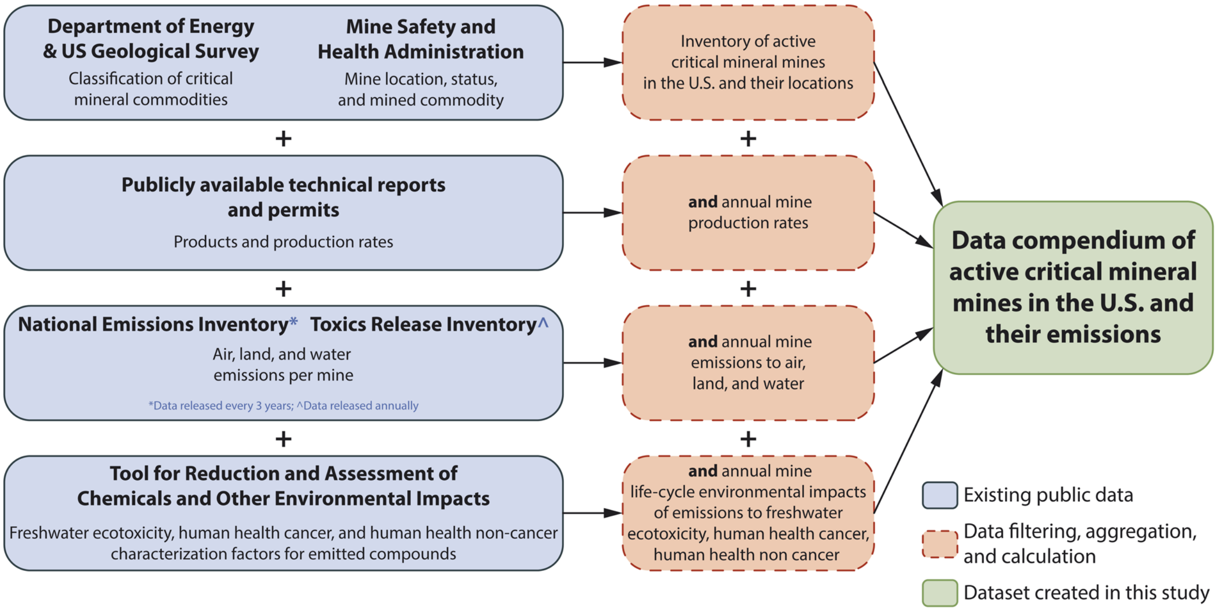

Fig. 1 Overview of underlying data sources within the data compendium of active critical mineral mines in the U.S.

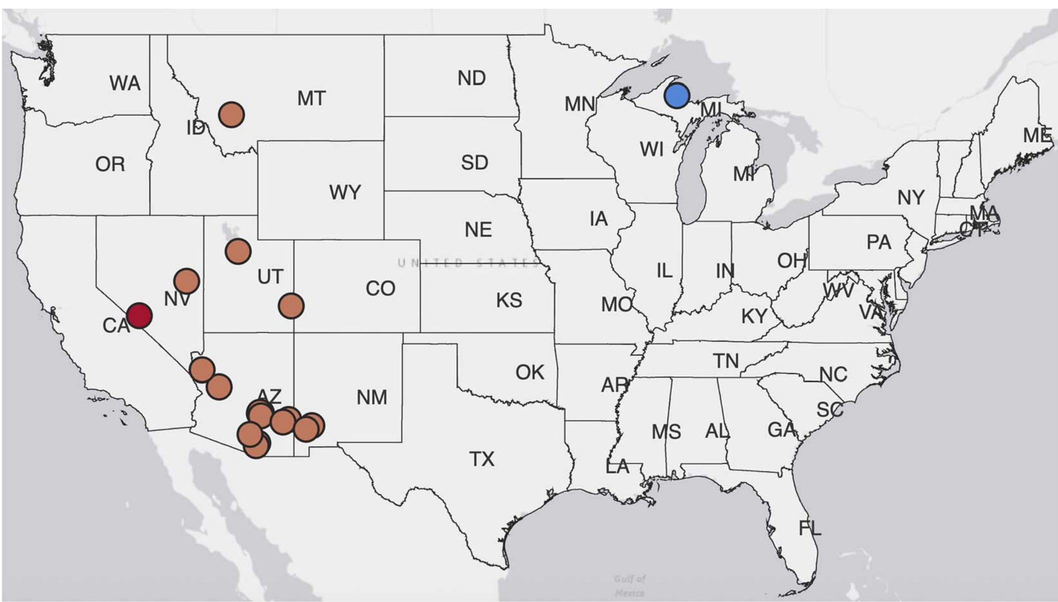

Fig. 2 Screenshot of interactive data compendium[29] (https://github.com/jenmbdunn/Critical_Mineral_Mines_Database).

minerals. It is important to note that closed mines might still release emissions through rain runoff or other methods,[30] but these emissions are not reported in the NEI or the TRI.

As of June 2025, the United States has 19 active critical mineral mines (17 copper; 1 nickel; 1 lithium). Most copper mines are in Arizona. The lone nickel mine, Eagle Mine, resides in Michigan's Upper Peninsula. The only operating lithium mine is Silver Peak Mine in Nevada. Silver Peak Mine historically was a silver mine but switched to lithium production in the 1960s. Annually, these mines produce 4.28 billion metric tons of mineral equivalent. A mineral equivalent is the amount of critical mineral contained in a product (*e.g.* the amount of copper embedded in a copper concentrate). More than 99% of this production is copper. The nickel and lithium annual production levels are significantly lower: 17 200 and 5000 metric tons of mineral equivalent, respectively.

The production of 4.28 billion metric tons of mineral equivalents emitted 225 million kg of pollutants into the environment, most of which were released into the soil (70%). These emissions also included 5.64 million tons of carbon dioxide equivalents (CO_2e), the standard unit for measuring global warming potential of GHGs. We estimate the largest impacts of critical mineral mine emissions are to ecotoxicity, ranging between 0.05 and 1.43 trillion CTUeco per year. CTU stands for comparative toxic unit. The impacts to HHNC and HHC were much lower, 22 to 28 thousand CTUnoncancer or CTUcancer per year. HHNC and HHC results are similar because most of the chemicals that the mines emitted and are included in TRACI had the same characterization factor for noncancer and cancer effects per kg of pollutant.

To understand the magnitude of these effects, we compared the effects of emissions from these mines to those from Dow Chemical's Freeport Plant in Freeport, TX. This chemical plant is the largest in the US and the 3rd largest globally.[31] We calculated the EC, HHNC, and HHC for this plant's emissions. globally.[31] We used the average of the IC ranges we calculated for mining activity as described above to reflect the impact of the mines in the compendium. The impacts of the critical mineral mines are equivalent to 1160 plants for EC, 2190 plants for HHNC, and 1490 plants for HHC. In this calculation, HHNC and HHC differ because many releases from the Freeport Chemical Plant had different characterization values for HHNC and HHC. These results indicate that the mining operations within the scope of this analysis contribute substantially to environmental pollution. Interestingly, the total GHGs emitted by the mines are only 1% of what the Freeport Plant emitted. The chemical industry, in general, relies on fossil fuels to create its products and often burns them to provide energy for their production, releasing large quantities of GHGs.[32]

Insights into the importance of recent, geographically-representative data

Given commonly-used LCI data sets generally use older data that may not be geographically representative, we explore data available for U.S. mines to assess the importance of the year and location data was acquired. Fig. 3 illustrates pollutant emissions to land per ton of copper from four mines. These mines – Bagdad, Morenci, Safford, and Sierrita – are copper mines in Arizona owned by Freeport-McMoRan. These mines all have a similar ore grade of approximately 0.3%.[33] The Miami mine, also in Arizona and owned by Freeport-McMoRan, was excluded from this analysis because ore extraction has stopped and only concentration and refining occur at the site. Out of emissions to air, land, and water, Fig. 3 only contains emissions to land because 99% of emissions from these mines were to land.

Except for the Safford mine, the relative emissions to land of each mine varied sizably from year to year. The annual emissions to land per ton of copper from Bagdad in 2023 were over five times greater than those from 2014, and nearly three times greater than those from 2018. The higher emissions – driven by emissions of lead compounds – were not an anomaly, but sustained starting in 2021. Production levels were consistent between 2020 and 2023, so the sharp uptick is not attributable to changes in mine throughput. Discerning the underlying source of lead emissions increases is difficult with only publicly available information at hand. Overall, the variations in pollutant emissions in Fig. 3 demonstrate risks associated with using outdated data. Using mining emissions data from 2020, as an example, might not be representative of emissions in 2023.

Further, the differences between emissions in Fig. 3 validate the need for spatially resolved data. In 2023, the Sierrita mine had twice as many emissions to land per ton of copper compared to the Morenci and Safford mines. The emissions from the Bagdad mine were double those of the Sierrita mine. Though these mines are in the same state, their relative emissions are undoubtedly site-specific, so the emissions data from one of these mines are not representative for the rest. Accordingly, there is also a risk in using datasets that aggregate data from a handful of mines and characterize the data as regionally or globally representative. This approach is currently very common in the LCA literature but is likely inadequate. In the case of this U.S. dataset, even at a more localized level (*e.g.*, state), one or two mines cannot represent the others.

Methodological considerations in using limited emissions data

A key methodological question arises when considering the data in Fig. 3. What should the spatial and temporal resolution be for LCI data used in LCAs of copper mining? In our view, this depends on the audience for the results. If the objective is to carry out an LCA of an individual mine for corporate use in

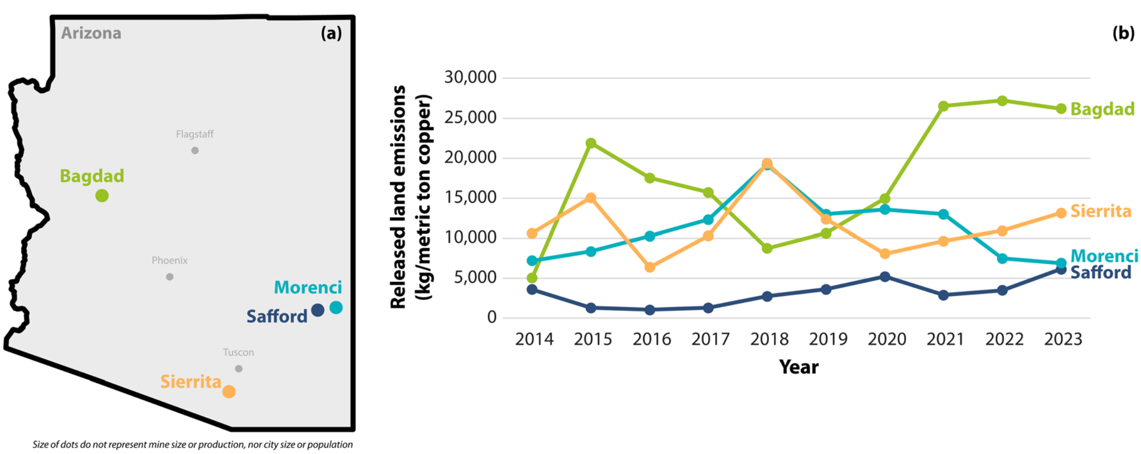

Fig. 3 Locations of Bagdad, Morenci, Safford, and Sierrita copper mines (a) and TRI land emissions per metric ton of copper produced (b).

reducing the environmental effects of hotspots, including in the supply chain to the mine, generating annual results (*e.g.*, use all LCI data for 2025) can be ideal. Alternatively, if the audience is the LCA community who need high quality LCI data for copper mining to be used as inputs to a host of LCAs of decarbonization, communications, or other technology, using an LCI data time series to generate probability distribution functions (PDF) for key parameters that reflects year-on-year fluctuations is likely more useful. Having access to annual (or more frequent) data allows the LCA community to develop these functions and incorporate them into LCA with Monte Carlo analysis or other means of incorporating the statistical characteristics of the data set to assess uncertainty.

The data gathered in the compendium can be used to develop probability distribution functions of emissions that can serve as recent, U.S.-specific inputs to Monte Carlo-based LCAs of mining in the U.S. For example, following the guidelines of Feng *et al.* (2024)[34] in establishing probability distribution functions based on relatively scarce data, an analyst could create a triangular distribution function for each of the mines in Fig. 3 which have 10 data points each. Feng *et al.*[34] recommend this distribution type for data sets with between 5 and 20 values and to use the minimum, maximum, and average as the minimum, maximum, and most probable values that define the distribution. If we wanted to create a probability distribution function for all Freeport-McMoRan Arizona copper mines, we could, per the Feng *et al.*[34] guidelines, use the 5th, 50th, and 95th percentiles from the data set for these values (Fig. 4). Choosing a triangular PDF using data from all four mines will capture the full spread of values from the mines, but if the Bagdad mine were not included in generating the PDF, the range of values in the function would be narrower and the LCA results would exhibit lower emissions.

Analysts could choose a different distribution function besides the triangle distribution based on characteristics of the data and statistical tests. For example, the log-normal

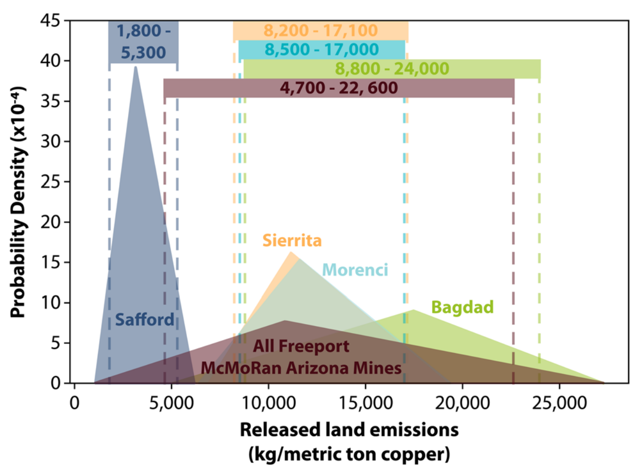

Fig. 4 Triangular distributions for the lead compound emissions to land per metric ton of copper for the Bagdad, Morenci, Safford, and Sierrita copper mines and for all four mines together. The dashed lines represent the range between the 5th and 95th percentiles.

distribution is an additional PDF option. Log-normal distributions can be appropriate because emissions data are intrinsically positive and often highly skewed from large, but uncommon, emissions releases.[35,36] The normal distribution is an option if an analyst does not know if outliers will be higher or lower than average. A normal distribution could, for example, be established by setting the minimum or maximum value three or four standard deviations away from the mean. However, it is important to note that a normal distribution does not intrinsically include only positive values. Depending on the standard deviation and mean, negative values can exist in the distribution. From an emissions viewpoint, this is illogical. As a final example, when many data are present, goodness-of-fit tests can be used to select a PDF. Wang *et al.*[37] determined that a Weibull distribution was the best fit for nitrous oxide (N_2O) emissions from corn farming in the ethanol supply chain after collecting N_2O conversion rates from 70 studies and applying goodness-of-fit tests to multiple distribution function options. When choosing a distribution, we urge analysts to consider how many data points exist. If there are less than 20 values, we echo Feng *et al.*'s recommendation of a triangular distribution.[34] If there are more than 20 values, we urge analysts to carry out goodness-of-fit tests to elect a distribution. Overall, data sets used to generate PDFs should be sufficiently temporally and spatially representative to address an LCA's goal and scope.

Given the drive to expand mining in the U.S. we sought to determine if we could estimate future impacts of new mines by investigating the correlations between production rates, total emissions, and emissions impacts (see Section S2). Initially, we found no correlation between production rate and emissions, nor between production rate and impacts. Excluding outliers, there are very weak positive correlations between these variables (Table S2). The lack of correlation emphasizes the locality and uniqueness of the impacts of each mine. There are hundreds of proposed critical mineral mines in the U.S.,[38] particularly lithium, copper, rare earths, nickel, and zinc mines. It is very unlikely that all mines will come into operation. Only about 45% of mineral discoveries convert to mines and begin production.[39,40] Undoubtedly, any new mines will emit pollutants, but the lack of correlation between production rate and emissions of the mines in the compendium signifies that we cannot predict the extent of these emissions and pollution.

Mines' effects on communities

Most active critical mineral mines are in the West. Eagle Mine is the only active critical mineral mine east of the Mississippi River. Extractive industries often situate themselves near low-income and/or disadvantaged communities because these areas offer the "path of least resistance", which frequently embodies less costly land and communities with limited power in decision making processes.[41,42] This pattern arises in the mines we have included in the compendium. 60% of the mines are in disadvantaged community tracts, 5% are in partially disadvantaged tracts, and 50% of mines located outside disadvantaged tracts are still within eight miles of a disadvantaged tract. 100% of mines are within 29 miles of a disadvantaged tract. Previous research has shown that some mining effects, such as deforestation, can extend up to 31 miles from a mine.[43] Communities near mines face a variety of environmental and health impacts, but the impacts are often unique to each community or area. For example, the communities near the Freeport-McMoRan copper mines in southern Arizona face elevated projections of wildfire and flood risk. Further, most of the communities near these mines are among the poorest in the nation in terms of income. 14 mines are within communities where income levels are at or below the national average. Proposed critical mines are scattered across the contiguous US and Alaska, but are disproportionally concentrated near Indigenous Reservations and traditional lands. In fact, the majority of critical mineral resources and reserves (97% nickel, 89% copper, 79% lithium, and 68% cobalt) in the US are located within 35 miles of Tribal Nations.[44,45]

Limitations

Our data compendium serves as an interactive aggregation of critical mineral mining data in the U.S. However, it is important to note that there are data limitations and gaps. For one, TRI data are released annually, but NEI data are released every three years. Our data compendium relied on 2023 TRI data, but on 2020 NEI data. The air emissions reflected from the 2020 NEI may not be fully representative of 2023 emissions. Another limitation lies within the TRACI database. Not all chemical compounds emitted from mines had corresponding characterization factors in TRACI. For example, particulate matter has no entries in TRACI, though it is known to affect ecosystems and human health.[46] Even if a chemical compound is included in TRACI, it may not have characterization factors for EC, HHNC, and HHC. For example, ammonia has a characterization factor for acidification, but none for EC, HHNC, and HHC. When these values were unavailable for ammonia or other chemical compounds, we assumed characterization factors of zero. It could be true that there is no impact of ammonia, or other chemicals lacking characterization factors, on EC, HHNC, and HHC, but this cannot be verified without additional toxicity studies. With these gaps, our work is likely an underestimate of the total impacts of mining emissions. For example, eight mines reported ammonia releases in the 2023 TRI, ranging from 270 to 7070 kg emitted into the air, but we assumed the impacts of these emissions had no detrimental effects due to lack of characterization factors. The compendium does not include values for energy or water consumption which companies are not required to report. Undoubtedly, a full LCI for an individual or representative set of mines would require these data. Pollutant emissions, however, are an essential yet often overlooked component of mining LCAs although communities near mines likely place a high value on reducing pollutant emissions which may even supersede energy consumption as a concern. Moreover, as in Ecoinvent and GREET, energy and water consumption can be estimated based on engineering models whereas pollutant emissions are more dependent on pollution control technology and management practices that may be site-specific. NEI and TRI data capture these differences.

Despite its limitations, the data compendium is a first-of-a-kind, valuable tool for researchers and communities. Researchers can leverage the data to explore additional trends between mining communities, emissions, impacts, and environmental justice. The data compendium can support local and tribal communities by providing centralized data sources and transparency about mining emissions.

Challenges in expanding the compendium beyond the U.S.

The data compendium currently only includes mines in the U.S. that produce critical minerals in EV batteries, namely, copper, lithium, and nickel. Expanding this data compendium to a global scale could guide increased transparency and scrutiny of the global critical mineral supply chain. However, undertaking a global critical mineral data compendium will undoubtedly be challenging. For one, there is no universal standard that outlines how mining data should be reported, what types of data should be included, and who reports these data. Adding data from other countries will require extensive investigation of data sources, understanding how these data are structured and reported, and scrutiny of the data quality within these sources. This process is lengthy and time-consuming. However, advances in artificial intelligence, machine learning, and large-language models could help expedite data collection. These challenges, however, assume that the data exist. Maus and Werner (2024)[47] report that over half of the world's mines are undocumented. There are many reasons a mine may be deemed undocumented. For one, artisanal and small-scale mining (ASM) is common practice in many countries – such as the Democratic Republic of Congo[48] and Peru.[49] However, ASM is often poorly regulated, or not regulated at all, which can result in lax data collection and documentation.[50] Another reason could be illegal mining. Illegal mining is unregulated and often conducted in areas with poor environmental and labor protocols.[50] If the mines themselves are not documented, their emissions and pollution are likely not measured either.

We note that sustainability reporting standards for the mining industry do not fill the LCI data gap for mines around the world. Two of the most relevant and popular standards are Copper Mark and the Initiative for Responsible Mining Assurance (IRMA). Copper Mark is an assurance framework to promote responsible mining practices across copper, molybdenum, nickel, and zinc supply chains.[51] IRMA independently assesses social and environmental performance at mine sites.[52] Whereas Copper Mark is limited to four mineral types, IRMA can be used by any mining company. Participation in Copper Mark or IRMA is completely voluntary. Mines that do participate in either program undergo an annual assessment. Environmentally, these assessments consider GHG emissions, air and water pollution, and water and waste management. For IRMA, GHG emissions must be publicly available either from the mine-site or at the corporate level. For Copper Mark, companies must calculate and disclose average scope 1, 2, and 3 emissions at the site-level. Pollution is an important consideration for both programs. IRMA has criteria relating to air and water quality. The chemical, biological, and physical conditions of surface water and groundwater and the changes to water quantity must be monitored and reported annually. There are no guidelines on monitoring frequency. IRMA tabulates water concentration limits and criteria for different water end-use (*e.g.* recreational, irrigation, *etc.*). For air quality, however, IRMA only requires that a mine's air quality management plan and compliance documentation is up-to-date and publicly available. Compliance documentation may include air quality monitoring data, but this is subject to environmental regulations of the country or region of the mine. A mine seeking IRMA certification can either use the European Union's air quality and rates standards or those determined by the host country. Pollution reporting for Copper Mark focuses more on risk assessment. Mines are required to establish baseline data for different pollutant emissions, such as those to air (particulate matter, sulfur oxides, *etc.*), water (oil and machinery fluids, waste runoff, *etc.*), soil and land (oil, fuel, and hazardous chemical spills), light, noise, and visual. With these baseline data, mines must publicly disclose risks and planned action to mitigate these emissions. In general, for both IRMA and Copper Mark, their environmental criteria do not require public reporting of the emissions. Often, communities must request that these data be released. Moreover, IRMA and Copper Mark do not house data. Analysts must go through company or mine-specific websites and dig through annual, financial, or other reported documentation to find environmental performance data.

Emerging methods to support mining sustainability standards and LCA

Emerging methods and technologies can capture real-time, localized emissions and impact data that could automate pollution data in support of mining sustainability standards and LCI data collection, especially for new mines. Satellite imagery processed with machine learning and artificial intelligence (AI) algorithms, for example, can provide insights into pollutant levels in the environment near mines. For example, Rowley and Karakuş[53] developed a model that can predict nitrogen dioxide, ozone, and particulate matter (PM_{10}) atmospheric concentrations from satellite imagery. PM_{10} emissions can be a substantial burden on communities near mines. The large, open-pit Morenci mine released nearly 3000 metric tons of PM_{10} in 2020. This mine sits a mere 10 miles away from the San Carlos Apache Indian Reservation. Nitrates can also be problematic releases from mines. For example, the Continental Mine in Montana and the Robinson Mine in Nevada emitted over 128 and 69 metric tons of nitrate compounds into water sources in 2023, respectively. Lioumbas *et al.* (2023)[54] offer a means to quantify nitrogen concentrations in water. They leveraged various models, such as algorithms and correlations over Sentinel-2 Multispectral Imagery bands, to estimate chlorophyll concentration in large bodies of water. These concentrations can arise from eutrophication driven by elevated nitrogen (such as nitrates) and phosphorus levels. Their method can also assess turbidity and hydrocarbon presence in water, both which could occur because of mines releasing pollutants. Satellite imagery can be collected at a higher frequency than reporting to governments or organizations like IRMA which can support near-term evaluations of mine's impacts that are not outdated. In addition, assessing historic imagery can help establish baselines of environmental quality, especially if imagery exists before a mine does.

Conclusion

LCA is touted as a tool to inform decision making in technology and policy development. Yet, using LCA in decision making requires the use of high-quality LCI data. Our development of a data compendium for the environmental effects of mining for copper, nickel, and lithium was motivated by our assessment of existing, commonly-used data sets for the raw material extraction phase of EV batteries, which revealed relatively low quality LCI data. These data were somewhat outdated and did not offer geographically representative pollutant emissions. The data compendium we have launched can fill this data gap. The data we compiled illustrates that temporal and spatial factors can strongly influence mines' emissions to water, land, and air. It is incumbent upon LCA practitioners to address these factors and account for them to the extent possible. Other areas of LCA, including those examining the effects of providing electricity for EVs based on local grid characteristics,[55,56] have undertaken very detailed examination of temporal and spatial factors. The raw material extraction phase should receive the same amount of attention and care.

Importantly, compiling these data in an open-access compendium can serve the needs of communities near mines. Ecoinvent access can cost thousands of dollars per year. Other large databases that host mineral production and operation data, such as S&P Capital IQ Pro or Bloomberg Terminal, also require costly subscriptions. These for-pay databases are exclusive to those that can afford them, often shutting out the general public and affected communities from understanding mineral production, operation, and impacts that are reported in these databases.

Open access to these data is essential for an informed public, especially because disadvantaged communities often bear disproportionate amounts of pollution from mining. Accessible data can support communities in engaging in permitting and other decision-making processes.

With the compendium's methodology and structure in place, we will expand the compendium to include data for other minerals mined in the U.S. and for other major mining countries including Chile (top producer of copper, second-leading producer of lithium)[21] and Australia (top producer of lithium)[21] that have public records.[57,58] Due to extensive mining in Chile and Australia, communities have voiced concerns about pollution, water availability, and other environmental impacts from critical mineral mining.[59] Plus, many mineral mines and deposits in Chile and Australia reside on or near traditional or Indigenous lands.[60–62] Analogous to the argument for the U.S. data compendium, it is imperative to maintain up-to-date and transparent databases of mineral production and pollution to inform surrounding communities on the impacts they may face. Additionally, we plan to update the data compendium as new mines begin production in the U.S. and with newly released TRI and NEI data.

Beyond supporting communities and other stakeholders, the availability of the compendium can ease the inclusion of pollution data into industrial and national strategies to reduce the environmental effects of the decarbonization technology supply chain. One example of this type of strategy is the European Union's Battery Passport. Currently, this program requires the reporting of a carbon footprint calculation for rechargeable industrial batteries with a capacity greater than 2 kWh[63] starting in February 2027.[64] The carbon footprint must be calculated and verified by a third-party agency and must include the four life cycle stages (raw material acquisition and pre-processing; main product production; distribution; and end-of-life and recycling). The use of company-specific data is mandatory for main product production, which embodies the assembly of battery cells and assembly of batteries with the battery cells and the electric components.[63] Company-specific data are not required for the other phases including raw material extraction despite the influence this stage can have on the overall sustainability of batteries. The existence of this compendium could help regulatory instruments like Battery Passport more easily include the raw material stage.

A second national strategy example lies in the Inflation Reduction Act (IRA),[65] passed in 2022. The status of this policy is in flux at the time of writing but overall, the intention of battery supply chain provisions in the IRA as passed helped motivate a domestic U.S. minerals supply chain by offering tax credits for electric vehicles with batteries that met mineral content criteria. Specifically, obtaining the tax credit required 80% of the market-value of minerals in the EV's battery to have been extracted or processed in the U.S. or with U.S. free trade partners or recycled in North America by 2027.[66] The IRA did not include any sustainability criteria, but supply chain sustainability data availability could support the expansion of this type of policy to quantitatively address supply chain environmental effects.

Finally, industry may opt to pursue more quantitative sustainability standards than currently offered by Copper Mark or IRMA and follow a path that the natural gas industry is pioneering. Specifically, this industry is building the structure to differentiate the market value of natural gas produced with lower life-cycle GHG emissions.[67] It is possible to envision a future in which minerals that are produced with low pollutant releases, low water consumption, and reduced energy consumption and GHG emissions compared to competitor minerals could secure a higher market value. This type of differentiation, however, requires the types of data the compendium gathers and would be best served by continued expansion of the compendium and its supporting data.

Abbreviations

ASM	Artisanal and small-scale mining
CAP	Criteria air pollutants
CTU	Comparative Toxic Unit
DRC	Democratic Republic of Congo
EC	Ecotoxicity
EJ	Environmental justice
EPA	Environmental Protection Agency
EV	Electric vehicle
GHG	Greenhouse gas
GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies
GSD2	Squared geometric standard deviation
HAP	Hazardous air pollutants
HHC	Human health cancer
HHNC	Human health non-cancer
IC	Impact category
IRA	Inflation Reduction Act
IRMA	Initiative for Responsible Mining Assurance
LCA	Life cycle assessment
LCI	Life cycle inventory
MSHA	Mine Health and Safety Administration
N_2O	Nitrous oxide
NEI	National Emissions Inventory
PDF	Probability distribution functions
PM10	Particulate matter, 10 microns or less in diameter
RoW	Rest of World
TRACI	Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts
TRI	Toxic Releases Inventory
U.S.	United States
USGS	United States Geological Survey

Author contributions

Jenna N. Trost: data curation, formal analysis, methodology, project administration, software, visualization, writing. Daniel Zitomer: data curation, formal analysis, methodology, software, visualization, resources. Natalia Gutiérrez Rodríguez: data curation, methodology, resources. Jennifer B. Dunn: conceptualization, funding acquisition, methodology, supervision, writing.

Conflicts of interest

There are no conflicts to declare.

Data availability

All data used in this study are available on GitHub at https://github.com/jenmbdunn/Critical_Mineral_Mines_Database. This study used publicly available data from the Mine Data Retrieval System at https://www.msha.gov/data-and-reports/mine-data-retrieval-system, National Emissions Inventory at https://www.epa.gov/air-emissions-inventories/2020-national-emissions-inventory-nei-data, the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts at https://www.epa.gov/chemical-research/tool-reduction-and-assessment-chemicals-and-other-environmental-impacts-traci, and from the Toxic Releases Inventory at https://www.epa.gov/toxics-release-inventory-tri-program/tri-toolbox.

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