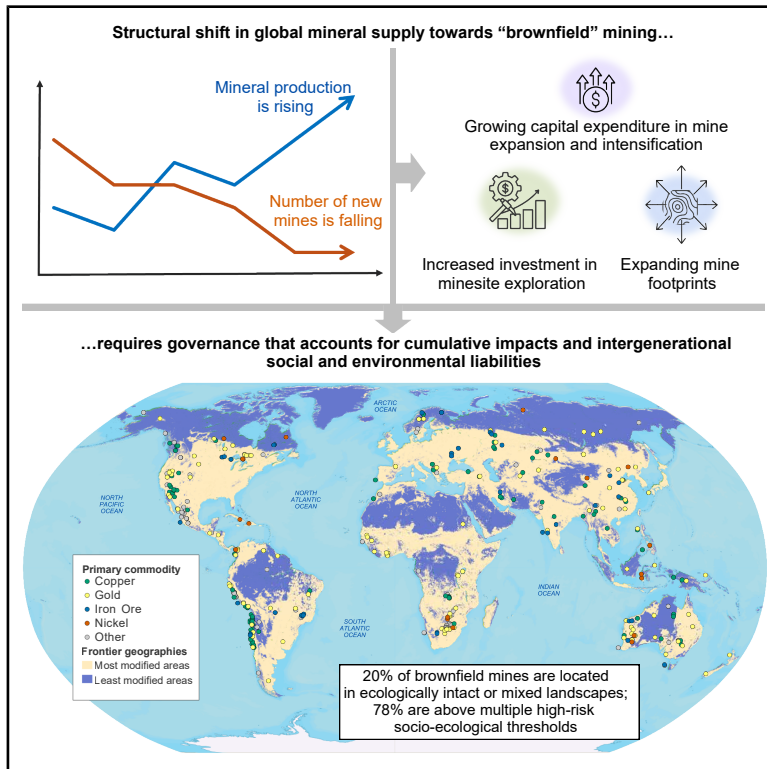


The rise of brownfield mining is reshaping global mineral supply and intensifying social and environmental risk

Graphical abstract



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In brief

Growing mineral demand and constraints on new mine development are reshaping the structure of the global mineral supply. However, the structural mechanism of these changes has not been made visible. Using global mineral production and capital-expenditure data from 1998 to 2024, we show that production growth increasingly depends on expanding and intensifying existing operations (i.e., “brownfield” mines). We identify 366 brownfield mines and show that many intersect with sensitive socioecological contexts, highlighting emerging risks and the need for governance attuned to cumulative impacts and long-term liabilities.

Highlights

- Global mineral supply increasingly relies on the expansion of existing mines
- 78% of brownfield mines exceed multiple socioecological high-risk thresholds
- 366 identified brownfield mines are concentrated in copper, gold, and iron ore
- As mines grow in both size and scale, mine closure is delayed and risks accumulate

Article

The rise of brownfield mining is reshaping global mineral supply and intensifying social and environmental risk

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SCIENCE FOR SOCIETY Mineral demand is rising worldwide for renewable energy technologies (e.g., solar, wind, and batteries) and other types of major infrastructure, such as transport, data centers, and digital devices. At the same time, controversy and complexity mean that building new mines is difficult, while metal recycling remains underdeveloped. These pressures are driving companies to intensify and expand extraction at existing “brownfield” mines—operating deeper, larger mines for longer periods. Yet, the extent of this shift, and how it contributes to accumulating social and environmental risk, remains elusive at global scale. We use more than 20 years of data on mining activity and capital investment to identify 366 brownfield mines that have expanded, with many located in socioecologically sensitive areas. Our results support policymakers and practitioners developing governance frameworks aligned with a future increasingly dependent on rising brownfield mining.

SUMMARY

Global mineral demand is rising faster than supply growth, driven by efforts to scale renewable energy, transport, digital, and defense infrastructure. Yet, new mine commissioning has slowed, with production growth sustained by “brownfield” mining—expanding and intensifying extraction at existing sites. Because mine expansion is considered routine industry practice, questions about the global scale and scope of brownfielding are not prominent in public discussion or scientific research, limiting our understanding of its socioecological risks. Here, we leverage global production, exploration, and capital-expenditure data from 1998 to 2024 to uncover a decade-long acceleration in brownfield mining. We identify 366 brownfield mines, with 20.5% in ecologically intact or mixed landscapes, 51.5% near biodiversity or protected areas, and 77.9% above multiple high-risk thresholds, with activity concentrated in copper, gold, and iron ore in Chile, the United States, and Australia. A greater dependency on brownfielding requires governance that accounts for cumulative impacts and intergenerational liabilities.

INTRODUCTION

Minerals and metals underpin construction, transport, defense, and digital infrastructure, and they are indispensable in the transition away from fossil fuels.^{1–3} Copper, cobalt, graphite, iron ore, lithium, nickel, zinc, and other minerals are essential to scaling up renewable energy infrastructure. While historical mineral production has broadly kept pace with rising demand,^{4,5}

projections show demand growing more sharply in the future.⁶ Lithium demand alone is expected to increase more than 5-fold by 2040 under stated policy scenarios.⁷ Growing demand reflects the mineral intensity of decarbonization technologies—electric vehicles require around six times the mineral inputs of conventional cars, and onshore wind turbines require significantly more minerals than gas-fired plants of comparable capacity.⁸

This sharp increase has unsettled the balance between mineral supply and demand.^{9,10} For copper and lithium, projected primary supply from announced mining projects will fall short of demand by 2035 under current policy settings.⁷ To maintain supply, developers are calling on governments to support mineral exploration and major project development.¹¹ Policy analyses suggest that governments in resource-endowed countries are focused on accelerating mining by streamlining approvals, fast-tracking strategic projects,^{11–13} and offering financial incentives to the sector.¹⁴ The prospect of more new mines developed faster is a growing concern for conservationists, local communities, and land-connected peoples. Some groups have called for mining “no-go” zones,^{15,16} while others press for stronger safeguards and the free prior and informed consent for mining on Indigenous peoples’ lands.¹⁷

Despite the policy focus on new mines, there is little evidence that new mines are coming online faster. Of 40 large-scale undeveloped copper ore bodies identified in 2018,¹⁸ only 4 have progressed to advanced development or production.¹⁹ Instead, the interval between discovery and production has lengthened, now averaging 15.7 years.²⁰ New large-scale mining projects across major commodities face a complex array of geological, geographical,²¹ social, environmental, and political risks.^{22–24} Rapid technological change also introduces market uncertainty by driving substitution, creating potential redundancies in future mineral demand.²⁵ As such, most new mineral supply is being sourced by expanding existing operations.

Mine expansion has long been central to the industry’s business model. Starting from a proven resource, growth routinely expands resource-reserve estimates and extends life of mine to leverage existing infrastructure and sunk capital.^{4,26,27} Mining companies also conduct mergers and acquisitions or enter joint ventures to optimize asset portfolios and create economies of scale. Another feature of the industry’s business model is deferring mine rehabilitation and final closure costs to manage cash flow²⁸ and maximize an asset’s net present value.^{29,30} This practice also sees the divestment of uneconomic assets before financial obligations fall due³¹ and can lead to the eventual abandonment of exhausted or uneconomic assets.³² Globally, relatively few large-scale mines have formally closed without ongoing liabilities.²⁹

The current trajectory will see mine closure increasingly deferred to the future to maintain mineral supply from existing operations. The sustainability risks of ongoing mine expansion and deferred and more complex closure are evident. As deposits decline in grade, expansions demand larger pits or deeper underground workings, resulting in greater volumes of mine waste,^{33,34} often extending environmental impacts, such as forest and habitat loss, beyond the original project footprint.^{35,36} Larger tailings storage facilities combined with climate change compound the risk of contamination of soils, rivers, and aquifers³⁷ and catastrophic industrial disasters.³⁸ For surrounding populations, mine expansion can also involve incremental disruption and displacement, with enduring social impacts.^{39–41}

These issues highlight the growing tension between the phenomenon of “brownfield” mining—the continuation, expansion, or intensification of mining activity at sites where financial capital has been sunk and mining has previously occurred²⁷—and the social and environmental risks it generates. At present, knowledge of the conditions driving the growth of brownfield mining

and the contexts in which it occurs is lacking. It is increasingly important to place brownfield mining into a broader global context—not only as a common industry strategy but also as a deepening structural feature of the global economy.

Here, we provide the first comprehensive view of brownfield mining at a global scale by demonstrating a clear trend toward brownfield mining over the last decade or so and show capital concentration geographically and in specific commodities. We also analyze the spatial embeddedness of brownfield sites within modified landscapes and characterize the contexts in which brownfield mines are located. Of the 366 brownfield sites in our dataset, at the level of the mine site, 20.5% are embedded within ecologically intact or mixed (i.e., partially modified) landscapes, increasing to 32.8% at regional scale; 51.5% are located within 20 km of a biodiversity hotspot or protected area and 77.9% are outside two or more high-risk thresholds. Our results also show that most of the mines are in contexts of high inequality, with a propensity for social conflict, and weak state institutions. By making brownfielding patterns more visible, this study brings into sharper focus the governance implications of a global energy digital transition, alongside growing military investment, that is increasingly reliant on mine expansion. In doing so, we respond to calls for the greater involvement of social and environmental expertise in debates about future mineral supply.⁴

RESULTS

Methods summary

To evaluate brownfielding patterns within the global energy and digital transition, we posed two research questions: (1) what are the temporal trends and spatial patterns of capital investment in brownfield mining? and (2) what are the social, environmental, and institutional implications of brownfield mining for host contexts? To explore these questions, we gathered data from the United States Geological Survey⁴² and the S&P Capital IQ Pro⁴³ to analyze brownfield mining and exploration trends across a relevant sample of commodities. Next, we categorized brownfield mines as a project type. A “brownfield” mine is distinct from a new mine (sometimes called a greenfield mine), which involves the initial development of a mine without a prior industrial-scale mining project. For the purposes of this study, brownfield mines are those that began operating before 2005, have declared reserves and resources, and received capital investment in one or more of the following five categories: physical “expansion,” “mine life extension,” “reopening” after suspension, “new zone development,” or “optimization.” Our analysis identified 366 brownfield mines that fit these criteria.

Finally, we examined the contexts within which these mines are located. Time-series satellite imagery was used to examine land-use changes in brownfield mining footprints. To analyze how these mines are spatially embedded across diverse landscapes, we developed a custom spatial layer of areas most and least modified by human activity. To probe the underlying conditions of host landscapes, we explored social and environmental risk in these contexts^{44–46} by linking mine location data to global datasets across three categories—societal stability, ecological context, and institutional effectiveness. Our method links mine location data with regional socioeconomic and environmental dynamics, situating these within broader debates on

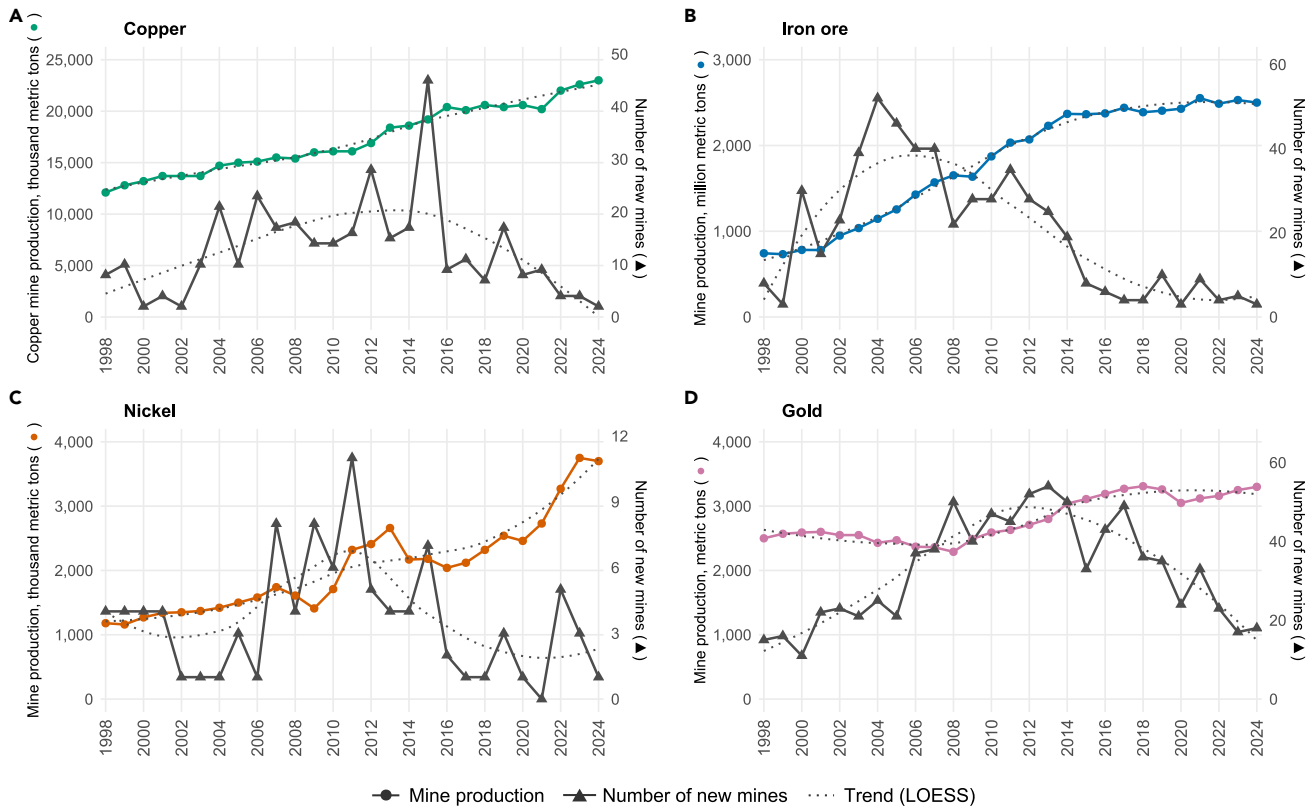


Figure 1. Mine production and new mines

Charts showing mine production over time and number of new mines that commenced production between 1998 and 2024 across selected metals: (A) copper, (B) iron ore, (C) nickel, and (D) gold. Trend lines were created by applying LOESS (locally eliminated scatterplot smoothing). Data are publicly available,⁴⁷ and see [methods](#) section on “[brownfielding temporal trends and spatial patterns](#).”

human rights and resource governance (see [methods](#) for more details).

Temporal and spatial patterns of brownfield investment

To characterize trends, we gathered global mineral production and new mine data for copper, iron ore, nickel, and gold from 1998 to 2024. [Figure 1](#) demonstrates overall increases in production alongside a corresponding decline in the number of new mines being brought into production over the last decade or so. The number of new mines peaked around 2015 for copper, in the early 2000s for iron ore, around 2010–2012 for nickel, and around 2012–2014 for gold. However, since these peaks, and the subsequent decline in the numbers of new mines, production has continued to rise. Copper, iron ore, and nickel reveal the inverse relationship of rising production with fewer new mines and where output is increasingly concentrated in large, long-life operations. This pattern is present but less pronounced in gold, reflecting its more fragmented industry structure, shorter mine lives, and non-manufacturing demand. Lithium does not currently follow this trend (presented in the figure in [Note S1](#)). Its historical uses differ from its more recent role in the energy transition, and supply-demand balance remains volatile.

This divergence between increasing production and fewer new mines is not being offset by recycling or waste revalorization, as these activities currently contribute only small volumes

to global supply, providing less than one-fifth of copper supply and 1% of lithium.⁴⁸ Instead, increased production is largely being driven by already existing mines through expansion of their physical footprint, processing capacity, or extension to mine life.

A capital shift away from new mine development and toward brownfield mining is also reflected in exploration investment, particularly among the world’s largest mining companies. Below, we use the S&P’s project stages: “grassroots” exploration denotes the earliest phases through to the initial quantification of resources; “late stage & feasibility” exploration refines, expands, and upgrades initial estimates, up to a positive production decision; and “minesite” exploration is conducted at or adjacent to an existing mine site, including searching for nearby satellite ore bodies.

Over the past 15 years, total exploration expenditure by major companies peaked in 2012, declined through 2016, and gradually increased from 2017, stabilizing at around USD 6 billion annually by 2022 ([Figure 2A](#)). However, the structure of this investment has changed. Over the 2010–2024 period, “minesite” exploration consistently comprised the largest share of investment (59.6% in 2024). Since 2016, “minesite” exploration has increased by 130%. By contrast, investment in “late stage & feasibility” and “grassroots” exploration remains smaller (18.7% and 21.7%, respectively) and has shown little absolute growth. Whether exploration is post-discovery or post-production,

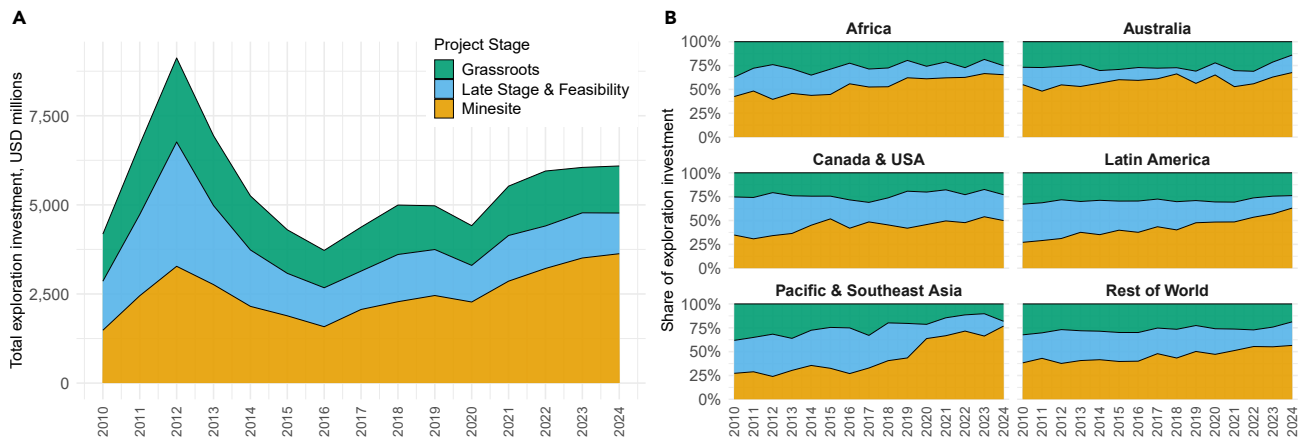


Figure 2. Mineral exploration investment

(A) Structure and change in exploration investment by major companies by project stage (2010–2024).

(B) Patterns of exploration investment by global region.

Data are publicly available,⁴⁷ and see [methods](#) section on “brownfielding temporal trends and spatial patterns.”

prioritization of “minesite” exploration is evident across key commodities and other types of entities (e.g., government-controlled entities) (see the figures in [Note S2](#)).

The pattern of increasing “minesite” exploration by major companies holds across all global regions ([Figure 2B](#)). The pattern is most pronounced in Pacific and Southeast Asia, where the share of “minesite” exploration rises from 27.3% in 2010 to 76.8% in 2024, alongside a marked decline in “late stage & feasibility” exploration. Africa and Latin America retain relatively larger “grassroots” exploration shares, signaling more early frontier activity. However, both also shift toward “minesite” exploration over time, increasing from 42.5% to 65.4% in Africa and from 27.1% to 63.0% in Latin America between 2010 and 2024. In Australia, “minesite” exploration dominates spending throughout the period, rising from the early 2020s as “greenfield” exploration declines. Canada and the USA lean more toward “late stage & feasibility” exploration, with “minesite” activity rising from 34.8% in 2010 to 49.9% in 2024. The rest of the world shows a similar pattern, increasing from 38.3% to 56.5%. Across all regions, the early 2020s mark a turning point: “minesite” activity rises, while “grassroots” exploration declines, indicating a reallocation of investment toward near-mine opportunities.

Overall, these patterns indicate that major companies are focused less on new discoveries to address supply shortfalls, noting that the discovery of “world-class” deposits is increasingly rare. These patterns also suggest a shift toward prioritizing sites with existing infrastructure that are lower risk and have sunk capital over those that may face greater financial or regulatory risk or social resistance.

To further explore brownfield mining trends and patterns, we analyzed capital investment flows into mines that began production before 2005, drawing on S&P project capital cost data. A significant shift is evident post-2005 ([Figure 3A](#)). Initial capital expenditure used to establish new mines has been followed by a surge in two other types of investment, which we categorize as “brownfielding” and “brownfielding enablers.” In the present study, “brownfielding” involves five categories of capital investment: physical “expansion” of the mine footprint or processing

capacity; “mine life extension,” which involves extending operations through deeper workings or underground phases; “re-opening” of mining after a period of suspension, care, and maintenance or major inactivity; “new zone development” through exploitation of adjacent ore bodies within the same reported project; and “optimization” to extend mine life. “Brownfielding enablers” are forms of sustaining or renewal capital (e.g., infrastructure upgrades, major equipment, or replacement works) that support continuing operations without expanding the physical footprint.

[Figures 3B](#) and [3C](#) disaggregate brownfielding capital investment by commodity and country. Overall, 80% of brownfielding capital is concentrated in copper (49.6%), gold (17.5%), iron ore (14.4%), and nickel (6.3%). Other contributors include platinum (3.8%), silver (2.7%), zinc (2.5%), lanthanides and lithium (0.9% each), and niobium (0.6%). Across minerals, brownfielding capital is dominated by physical “expansion,” followed by “new zone development” and “mine life extension,” while “optimization” and “reopening” are comparatively small. At the country level ([Figure 3C](#)), Chile leads global brownfielding investment with 25.2% of total capital, followed by the USA (11.4%), Australia (10.1%), and Indonesia (9.1%). While brownfielding is a dominant trend, patterns vary by jurisdiction. Countries like Chile, Australia, Peru, and Brazil are more expansion driven. On the other hand, in Indonesia, “optimization” dominates, and “mine life extension” is more prevalent in Canada, the USA, and South Africa. These variations reflect mineral endowments, corporate strategies, and differences in host contexts.

The global distribution of the 366 brownfield mine sites that we identified ([Figure 4A](#)) reveals the extent of this strategy, with 36 sites in Australia, 32 in the USA, 31 in South Africa, 31 in China, 23 in Peru, 22 in Canada, 19 in Mexico, 16 in Russia, 14 in Brazil, and 111 mines spread across 48 additional countries ([Figure 4B](#)). These sites account for 57.0% of global platinum production (e.g., Marikana and Impala in South Africa), 41.3% of copper (e.g., Escondida in Chile and Grasberg in Indonesia), 37.7% of lithium (e.g., Greenbushes in Australia and the Salar de Atacama in Chile), 25.3% of iron ore (e.g., Hamersley and Yandi in

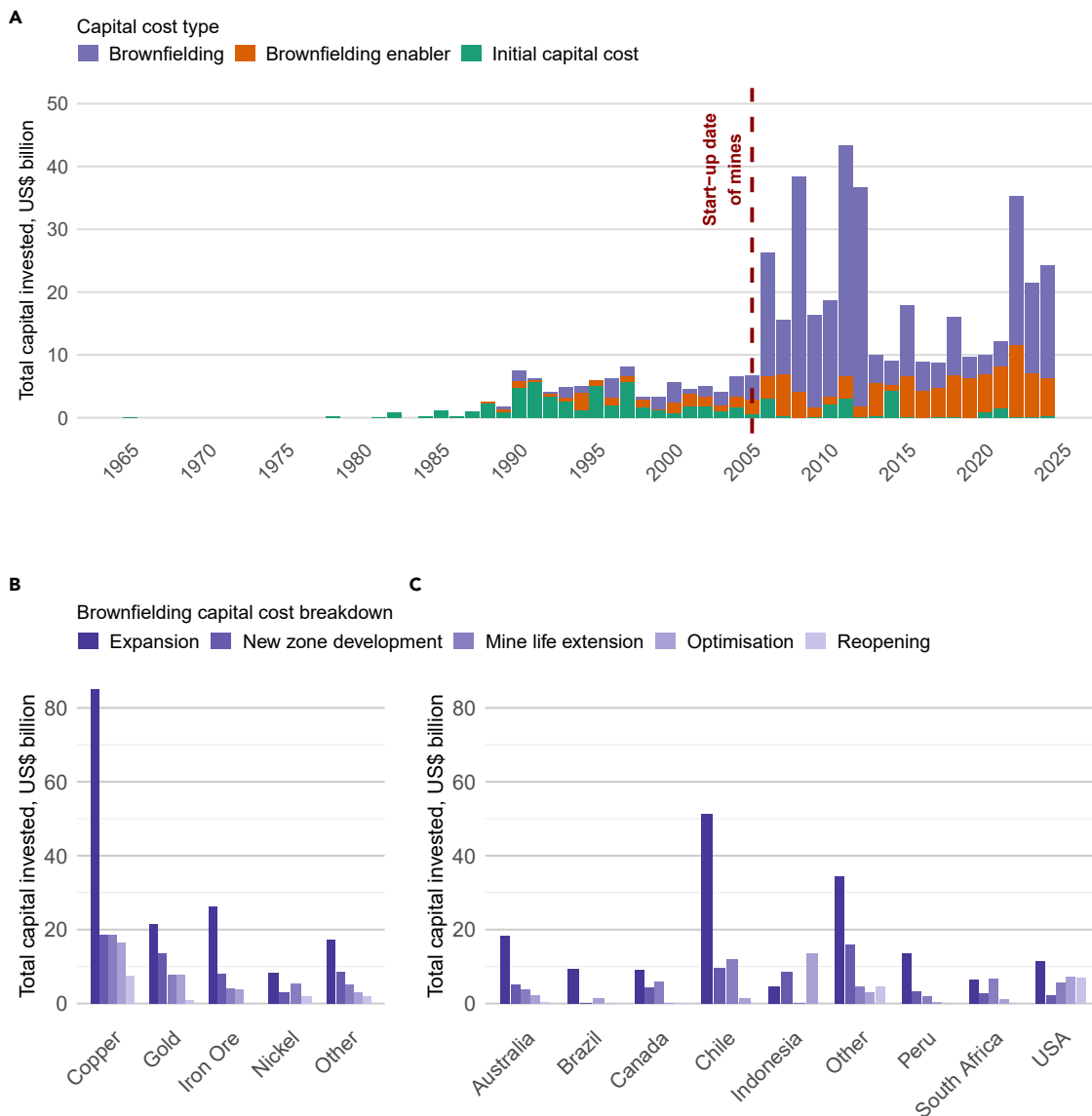


Figure 3. Brownfielding and invested capital

(A) Change over time in capital invested into mines commencing in 2005 or earlier.

(B) The total brownfielding capital cost breakdown by commodity (shown commodities account for 80% of global brownfielding capital investment for all years).

(C) The total brownfielding capital cost breakdown by country (countries displayed account for 80% of global brownfielding capital investment for all years).

Data are publicly available,⁴⁷ and see [methods](#) section on “[brownfielding temporal trends and spatial patterns.](#)”

Australia), 22.3% of zinc (e.g., Rampura Agucha in India and Red Dog in the USA), and 17.1% of nickel (e.g., Jinchuan in China and Sudbury in Canada) (Figure 4C).

Taken together, the results show the breadth and variation of brownfielding activity globally. Hundreds of pre-2005 mines remain sites of major new capital investment, accounting for a large share of production across major, high-volume commodities.

Spatial embeddedness and contexts of brownfield mines

The physical expansion of mine footprints under brownfield development is identified using satellite imagery. From the global

dataset of 366 brownfield operations, we selected 6 mine sites to explore and illustrate in more detail to reflect diversity in commodity type, geographic location (country, continent, and Köppen climate zone), investment scale, and the visibility of spatial expansion in satellite imagery (see [methods](#) and [Note S4](#)). The selected sites are Sepon (Laos), Mogalakwena (South Africa), Mt. Tom Price (within the Hammersley Consolidated complex, Australia), Turquoise Ridge (within the Nevada Operations complex, USA), Voisey’s Bay (Canada), and Porgera (Papua New Guinea). Figure 5A illustrates changes in the footprint size of these mines between 1990 and 2024 using time-series imagery, exhibiting expansion in mine pits, spoil piles, infrastructure, tailings storage facilities, and other mining infrastructure. Figure 5B

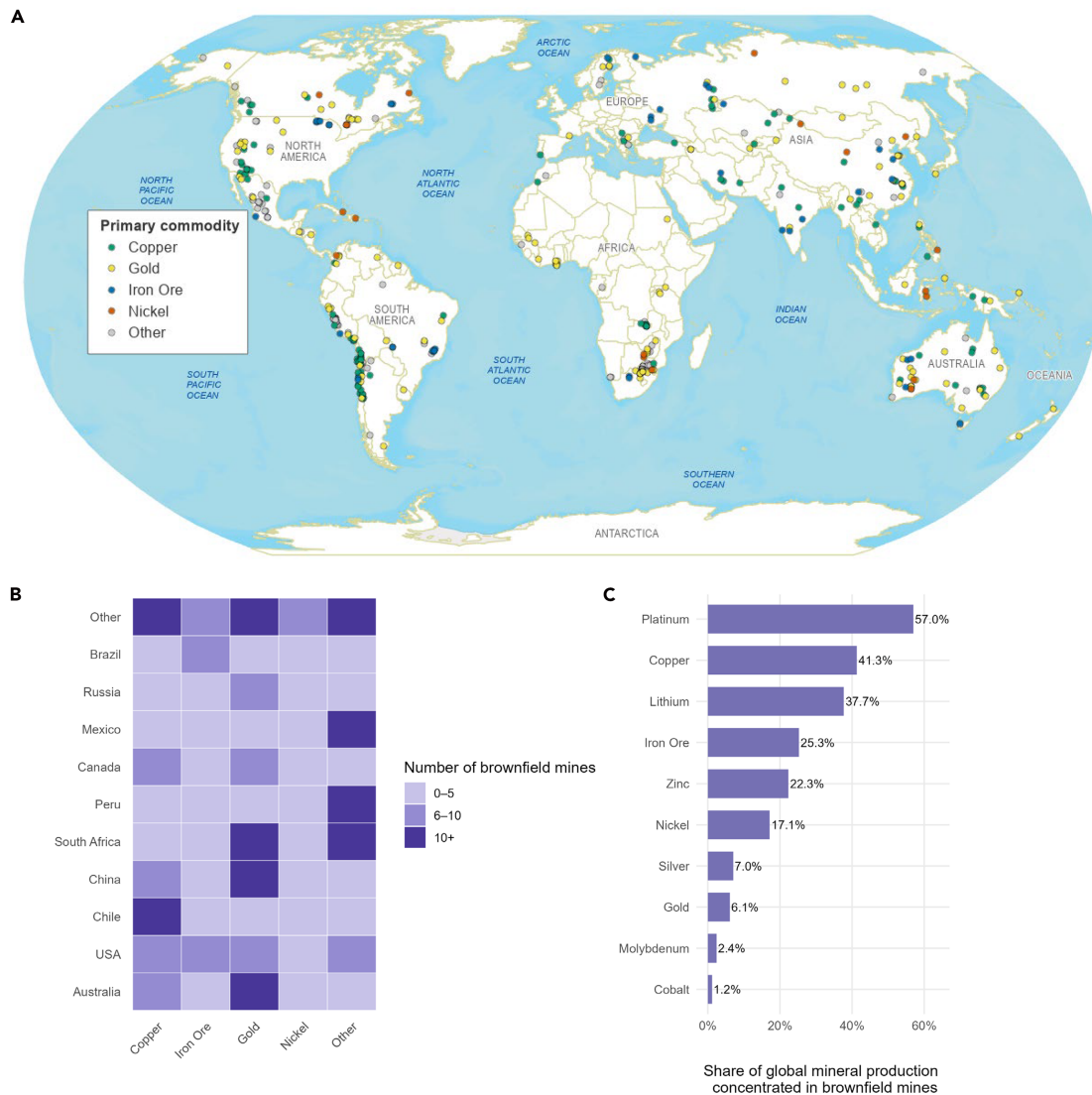


Figure 4. Brownfield mines

(A) Global distribution of brownfield mines.

(B) Distribution of brownfield mines by mineral and country.

(C) Concentration of global mineral production in brownfield mines.

Data are publicly available,⁴⁷ and see [methods](#) section on “[brownfielding temporal trends and spatial patterns.](#)”

shows how expansion trajectories vary across sites over time and space. While sites like Mogalakwena, Sepon, and Turquoise Ridge have more than doubled in area, others, such as Porgera, have expanded more gradually as they expanded their underground operations. Notably, none of the sites show evidence of footprints reducing in size.

To further examine the embeddedness of brownfield mine sites within modified landscapes at the global scale, we developed a custom spatial layer of frontier geographies, distinguishing “most modified” (i.e., heavily disturbed areas) and “least modified” (i.e., more ecologically intact areas) land areas based on climate zones, existing level of human modification, and the extent of croplands and pastures (see [methods](#) and [Note S5](#)). We intersected the custom layer with the locations of the 366

brownfield mine sites and analyzed their spatial embeddedness to understand how mining interacts with, and contributes to, land-use dynamics locally and regionally ([Figure 6](#)).

As [Figure 6A](#) demonstrates, a majority of the 366 brownfield sites are situated in highly modified landscapes that overlap with human settlements, agricultural zones, and other industries and infrastructure, exemplified in [Figure 6B](#) by Turquoise Ridge (USA) and Mogalakwena (South Africa). In contrast, some mines intersect with relatively undisturbed landscapes such as the Arctic tundra, forested regions, deserts, and high-mountain areas, exemplified by Porgera (Papua New Guinea) and Voisey’s Bay (northern Canada) ([Figure 6B](#)). Other mines are situated within mixed (partially modified) forms of modification, for example, Mt. Tom Price (Australia) and Sepon (Laos) ([Figure 6B](#)).

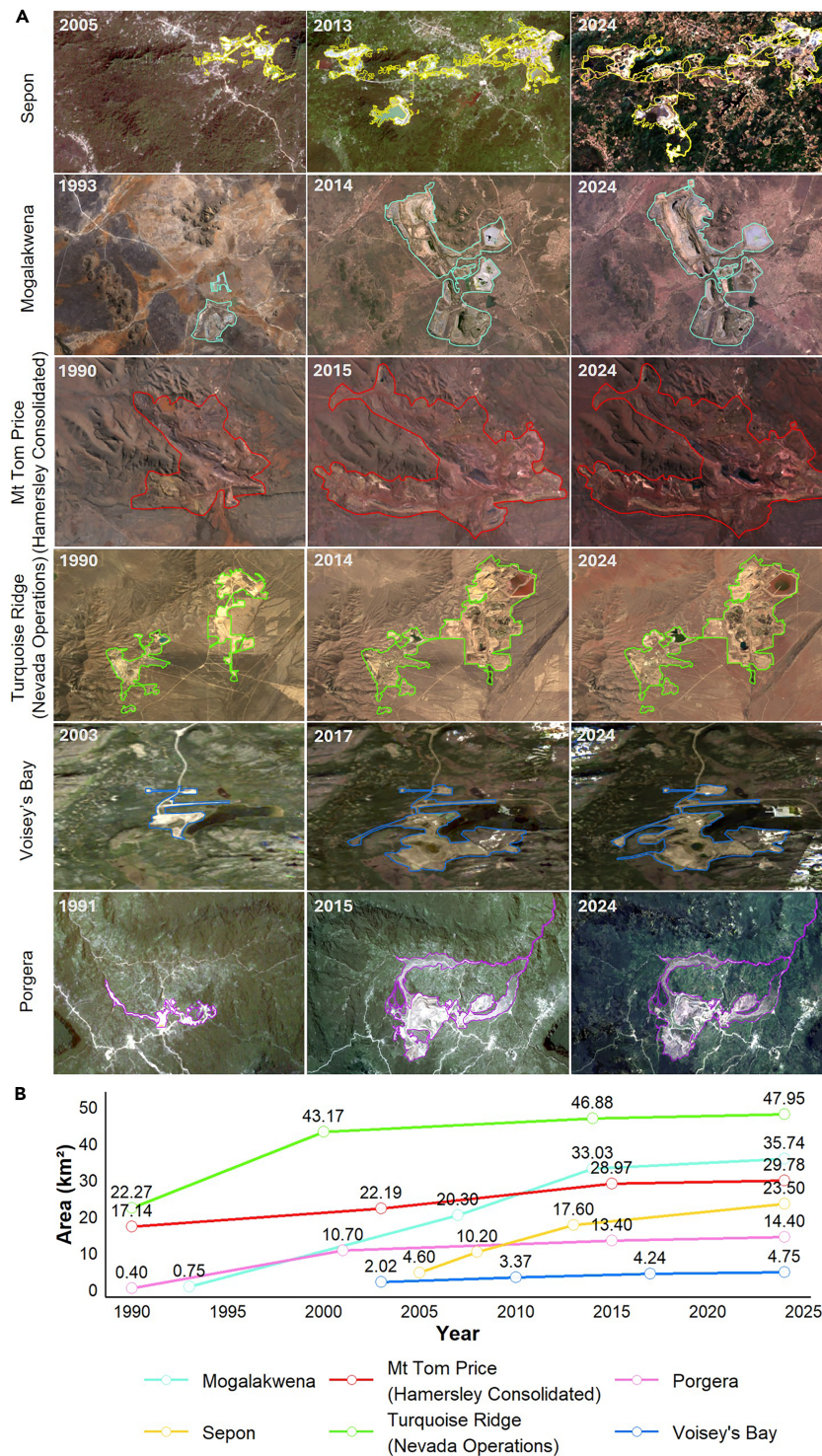


Figure 5. Expansion of mining footprints at brownfield sites

(A) Landsat and Sentinel satellite imagery with delineated progressive expansion of mining footprints at six representative sites: Sepon (copper, Laos), Mogalakwena (platinum, South Africa), Mt. Tom Price (part of Hammersley Consolidated, iron ore, Australia), Turquoise Ridge (part of Nevada Operations, gold, USA), Voisey's Bay (nickel, Canada), and Porgera (gold, Papua New Guinea).

(B) Graph of the cumulative increase in mining area (km²) for the six mining sites. Data and method: see [methods](#) section on “[spatial and contextual analysis](#)” and [Note S4](#).

Figure 6C quantifies the “gradient” of spatial embeddedness of brownfield mines within modified landscapes by showing the distribution of the proportion of most-modified areas for all brownfield mines as a function of distance from each site to capture “mine-site” (5 km), “local” (25 and 50 km), and “regional” (75 and 100 km) land-use dynamics. These data reveal wide vari-

ability across the dataset. Overall, 291 of the 366 brownfield sites (79.5%) are located within predominantly modified landscapes (where more than 80% of the 5-km mine-site area is classified as most modified). This proportion remains consistently high but declines slightly with distance, from 70.5% locally (25–50 km) to 67.2% regionally (75–100 km).

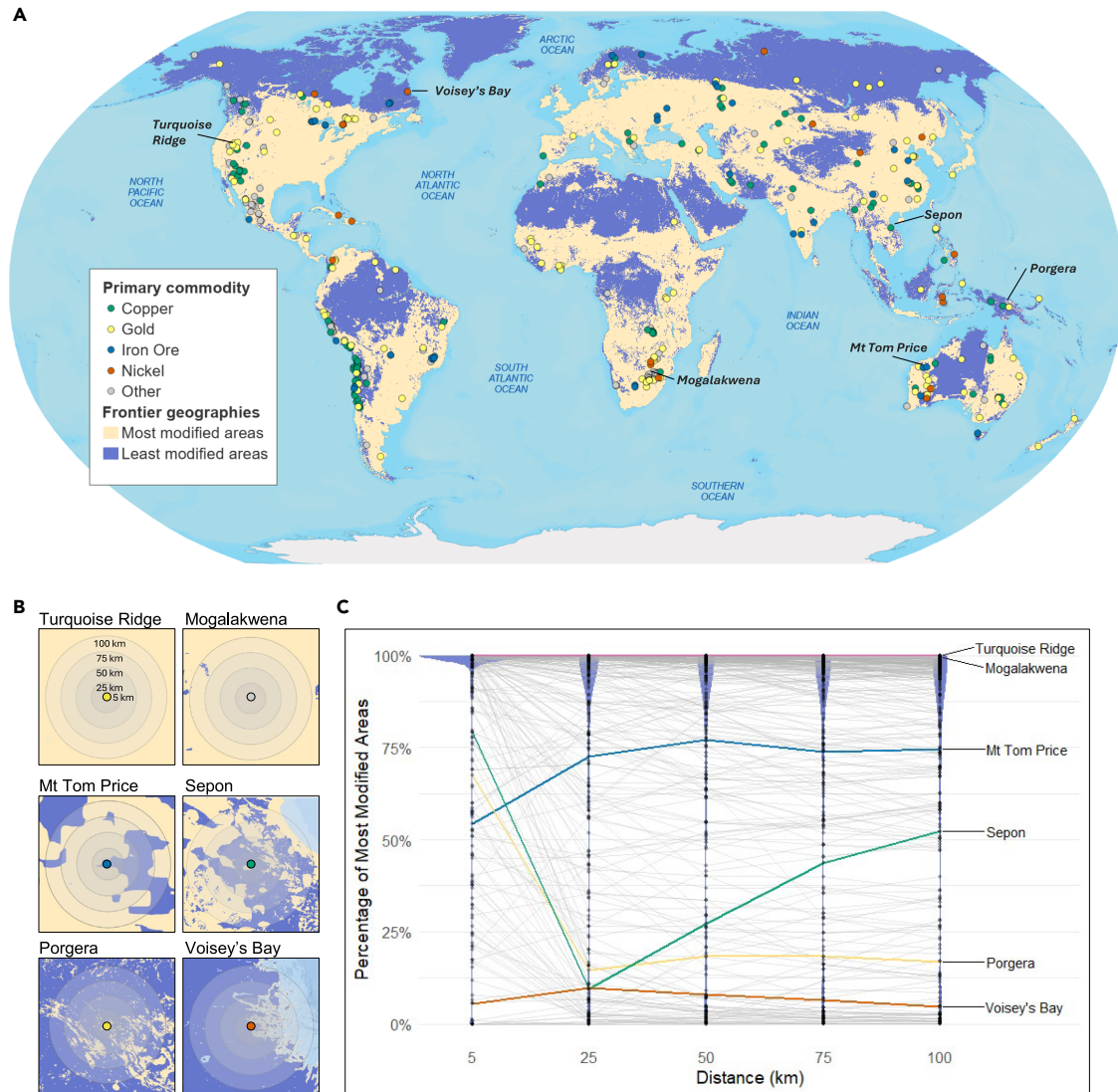


Figure 6. Brownfield mines in modified landscapes

(A) A spatial overlay of brownfield mine sites (point color disaggregated by commodity) with frontier geographies classified as least (purple) and most (pale orange) modified, highlighting the location of six selected mines: Sepon (Laos), Mogalakwena (South Africa), Mt. Tom Price (part of Hamersley Consolidated, iron ore, Australia), Turquoise Ridge (part of Nevada Operations, gold, USA), Voisey's Bay (Canada), and Porgera (Papua New Guinea).

(B) Spatial embeddedness (within 5, 25, 50, 75, and 100 km buffer differences) of the six selected mines across least and most modified landscapes.

(C) The combined line and violin chart quantifies the distribution of the percentage of most-modified areas at increasing distance (at 5, 25, 50, 75, and 100 km buffer differences) from each brownfield mine site, with the six selected mines highlighted.

Data are publicly available,⁴⁷ and see [methods](#) section on “spatial and contextual analysis.”

In contrast, 75 sites (or 20.5%) are located within ecologically intact or mixed landscapes (increasing to 32.8% at the regional scale). Among these, 20 brownfield mines (5.5%) are located within predominantly unmodified landscapes (where more than 80% of the 5-km mine-site area is classified as least modified). Examples include Red Dog (USA), Svartliden (Sweden), Lunnoye (Russia), Voisey's Bay (Canada), Mt. Muro (Indonesia), Ok Tedi (PNG), and Salar del Hombre Muerto (Argentina). These mines commenced as open pit mines, with Svartliden and Lunnoye now also using underground mining and Voisey's Bay undertaking major underground expansion to extend its life. The share of

mines embedded in least-modified landscapes increases with distance: 5.5% at mine-site scale (5 km), 13.0% locally (25–50 km), and 13.5% regionally (75–100 km). Mines such as Voisey's Bay and Porgera display low percentages of modification at both local and regional distances.

A further 55 mines (15.0%) are situated within landscapes characterized by mixed levels of modification. This proportion increases to 16.5% locally (at 25–50 km) and 19.3% regionally (at 75–100 km). The dynamics of mixed land use are site specific and change with distance. For example, at Mt. Tom Price the proportion of most-modified areas rises from 54.3% at the

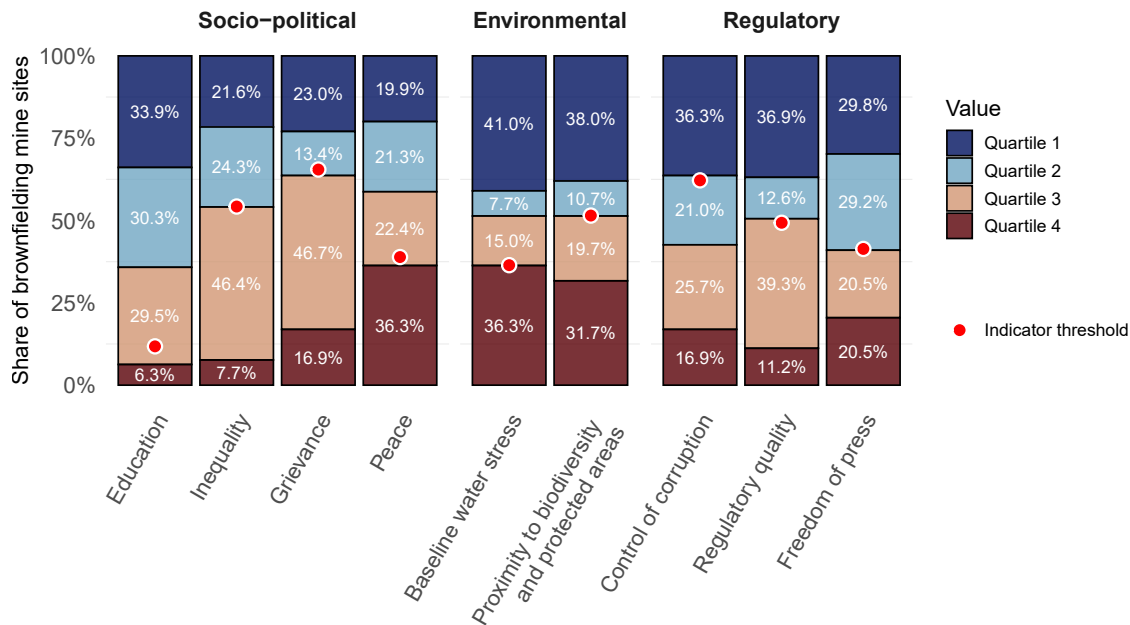


Figure 7. Distribution of brownfield mine sites across global sociopolitical, environmental, and regulatory indicators

Bars show the share of sites falling into quartiles for each indicator. Color represents quartiles from most adverse (quartile 4, dark red) to least adverse (quartile 1, dark blue). The red dot marks the designated high-risk threshold for each indicator. Data are publicly available,⁴⁹ and see [methods](#) section on “[spatial and contextual analysis](#).”

mine site to 72.5% locally and 77.2% regionally. In contrast, at Porgera there is a steep decrease from 67.6% at the mine site to 14.6% locally, followed by a slight increase to 18.5% regionally. The curve for mines like Sepon rises after 25 km, indicating that, while its immediate vicinity has a relatively low proportion of mostly modified land, the broader region becomes increasingly modified. This also indicates that Sepon is in a landscape where local ecological integrity is only moderately altered and that its regional context faces greater anthropogenic pressures.

To more fully understand the contextual conditions in which brownfielding occurs, we analyzed the spatial intersection of the 366 sites with nine global indicators grouped into three categories: “sociopolitical,” “environmental,” and “regulatory” (Figure 7). These indicators provide insight into the institutional, social, and ecological contexts in which brownfielding is unfolding without making causal claims about project-level performance or outcomes. Together, they support examination of the conditions under which brownfielding occurs—including the strength of institutions, pressures in host localities, and prospects for public accountability.

Of the 366 brownfield sites analyzed, 43 (11.7%) are in countries where average years of schooling are 8 or less, reflecting very low levels of formal education (countries with the highest number of brownfield mines outside the designated high-risk threshold are Zambia, India, and Ghana). More than half of the sites (198, 54.2%) are in countries with high levels of structural inequality (measured by the Fragile States Index) (e.g., South Africa, China, and Peru), and 239 sites (65.5%) are in contexts with elevated levels of group grievance (e.g., USA, South Africa, and China), indicating internal divisions along social or political lines. Additionally, 142 sites (38.9%) are in countries flagged for con-

flict, societal safety, or militarization (e.g., South Africa, Mexico, and Russia), exceeding the Global Peace Index threshold of 2.372.

Environmental risks are also present. One-third of sites (133, 36.4%) are in areas classified by the World Resources Institute’s Aqueduct Water Risk tool as facing water availability that is “extremely high” or “arid and low” (e.g., China, Australia, and South Africa). Moreover, 188 sites (51.5%) are within 20 km of biodiversity hotspots or protected areas, highlighting the proximity of brownfielding projects to ecologically sensitive environments (e.g., USA, Australia, and South Africa).

From a regulatory perspective, 227 sites (62.2%) are in countries with poor control of corruption (e.g., Peru, Mexico, and Russia), defined by a score of ≤ 0 in the Worldwide Governance Indicators dataset. A further 180 sites (49.3%) are in jurisdictions assessed to have weak regulatory quality (e.g., South Africa, China, and Mexico), again based on scores ≤ 0 . In terms of freedom of expression and public oversight, 151 sites (41.4%) are in countries with a press freedom score below 55.2 (e.g., China, Peru, and Mexico), according to Reporters Without Borders, indicating that mining-induced impacts and harms may be less visible or systemically underreported.

The data show that 284 (77.9%) of the 366 brownfield sites are situated in jurisdictions where two or more of these indicators fall outside the designated high-risk thresholds. Half of the sites (54.1%) have at least five of nine indicators outside the thresholds, with the highest number of sites (at least 10) located in South Africa, China, Mexico, Russia, Peru, and Brazil. This suggests that brownfielding often proceeds in settings where institutional or environmental conditions pose major challenges to operators, regulators, and affected people.

DISCUSSION

Results in context

Research by geo- and spatial scientists has drawn attention to mining's expanding footprint and tied mine extent to production volume.⁵⁰ We complement this work using capital investment data, where we find that increased production is not only expanding footprints but also intensifying pressures in land-use frontiers. Our results depict a distinct uptick in the last decade or so in capital investment toward brownfield mining; that is, into mines where major capital has already been sunk. While geoscientists and industry specialists have called for the earlier delineation of potential mine extents and improved environmental impact assessment,^{4,23,27} there is a tendency to normalize brownfield mining as standard practice and overlook its cumulative consequences. Our approach is different. Rather than call for mine-site improvements within the context of a broader mining acceleration agenda, we call for a reframing of brownfield mining as a systemic sustainability challenge. Further, instead of presuming that brownfield mines have a lower risk profile than new mines, we probe this increasingly prominent phenomenon at a global scale to elicit patterns and insights for host communities, policymakers, and institutions.

Globally, land-use expansion is closely tied to sustainability concerns ranging from climate change to biodiversity loss and human rights challenges.⁵¹ Land-use expansion concentrates in so-called “frontier geographies”—places marked by land-use transformation through resource exploitation.^{52,53} Our results show that capital concentration is most pronounced in copper, gold, and iron ore and geographically in Chile, the USA, and Australia. The energy and digital transitions are mineral intensive, while global economic uncertainty alongside complex geopolitics^{54–56} will see risk and cost containment dominate corporate priorities in the near to medium term. In this context, brownfield mining is an appealing option, as it maintains production and offers stronger return on investment and fewer financial and regulatory risks than establishing new mines while deferring closure commitments and related costs. Regulators and other parties that are focused on fast-tracking new mines may not be sensitized to the rise of brownfield mining. To address this, we argue that this phenomenon warrants a far more integrated research and policy agenda than currently exists.

Research and policy implications

Our findings carry several implications for how the social and environmental risks of brownfield mining are understood and governed.⁵⁷ These implications begin to connect the analysis of mineral supply and mine-site footprints to issues that have received less attention in global debates about the energy transition—questions that relate to history, harm, human rights, and the persistence of mining frontiers.

Desensitization and invisibility

At the 5-km mine-site level, our results show that 5% of brownfield mines are located within ecologically intact or “least-modified” areas, where mining is the primary driver of frontier formation. The areas around these mines are clearly important from a conservation standpoint. By contrast, 79.5% of brownfield mines are located in highly modified landscapes, where there

is less ecological value left to protect and where conservation “wins” (e.g., ecosystem reconstruction through mine rehabilitation) may be harder to achieve. However, our gradient of spatial embeddedness brings nuance to these findings. Although only 20.5% of our dataset is embedded within ecologically intact or mixed landscapes at the 5-km gradient, this increases to 32.8% with distance (i.e., extending the analytical buffer zone). On this gradient, brownfield mining eventually intersects meaningfully with less disturbed landscapes within the broader areas. If conservationists and policymakers assume that brownfield mining is a “lesser evil” than establishing a new mine, they may miss some of the deeper, accumulating social and environmental risks of this practice. As with new mines, brownfield mining is frontier-making, and it is on the rise, albeit in a more embedded and often in a less visible way.

Where expansion intersects with high inequality, weak institutions, or fragile environments, social and environmental risks compound further. Of the 366 sites in our dataset, 77.9% are outside two or more high-risk thresholds across the nine global indicators. Brownfielding in contexts with multiple situated risks^{9,31,50} can deepen human exposure to mining risks and intensify economic dependency—even when projects deliver positive financial returns for governments, shareholders, or other parties through royalties, taxes, jobs, and other financial flows. Some researchers argue that these benefits can work to desensitize some parties to accumulating liabilities.⁵⁸ In contrast to the public attention that new mining projects attract, late-stage changes that facilitate brownfielding may not be as openly negotiated nor as visible.

The public record shows how historical harms and impacts can become “invisible.”⁵⁹ The destruction of Juukan Gorge in Western Australia is one example, where, in 2020, Rio Tinto legally blasted a 47,000-year-old Aboriginal heritage site to access iron ore, illustrating how cultural significance can be erased in the pursuit of mine expansion.⁶⁰ An estimated majority of transition-relevant minerals are located on Indigenous peoples' lands globally.⁶¹ Recent reports show that Indigenous perspectives represent a small fraction (2%) of media coverage on the energy transition.⁶² At the same time, civic space is under threat. At least 146 land and environmental defenders were killed in 2024, with extractives the leading sector implicated.⁶³ Patterns of invisibility and institutional forgetting sit uneasily with the idea of a “just” energy transition.⁶⁴ Tracking underlying conditions such as inequality, freedom of the press, and peace provides important perspectives as mine footprints expand and intensify to meet growing mineral demand.

Other extensions of the mining frontier

Mining capital investment trends and spatial analysis provide strong indicators of brownfield mining as a growing phenomenon. However, some forms of brownfielding are hard to detect through spatial analysis and may appear, at first, to lie outside scope. Underground expansion is one such example. Spatial analysis can capture surface land-use change, but it does not capture underground workings. Turquoise Ridge, for instance, is a largely an underground mine with some open pit. Porgera expanded underground in 2002, and both Mogalakwena and Voisey's Bay are expanding underground. Likewise, the vertical expansion of waste dumps and tailings storage facilities is undetected through spatial analysis, calling for elevation modeling to provide a more complete picture of brownfield mining's effects

globally. Our methodology provides an avenue for detecting the less visible forms of brownfield mining.

Circular economy strategies may also, at first, appear to fall outside the scope of brownfielding. In some contexts, circular economy approaches can mitigate pressure on undisturbed landscapes.⁶⁵ However, other strategies, such as by-product recovery and waste remining,⁶⁶ can function as an extension of the mining frontier, while removing only a small proportion (say <1%) of material. Remining typically requires new land, water, and energy inputs and rarely resolves legacy harms. Likewise, mined land repurposing, such as converting previously mined land to a large-scale solar park, can limit or sterilize land use for other purposes and does not always benefit mine-affected communities who can remain in a state of energy poverty.^{67–69} In other words, circular economy practices do not necessarily offset the systemic liabilities of deferred mine closure and cumulative disturbance. Our findings suggest that the structural dependence on brownfield mining is currently outpacing institutional capacity to govern its social and environmental consequences.

Industrial disasters provide another, less predictable, example of mine continuation that expands the brownfield effect. Major industrial accidents are often assumed to bring mining to a halt but, in practice, they tend to suspend or redirect mining activity. In 2025, at the giant Grasberg copper and gold mine in West Papua, production resumed after a fatal waste-related incident despite a declaration of force majeure.⁷⁰ Likewise, the Samarco tailings disaster in Brazil paused operations, but mining has recommenced even as legal proceedings remain unresolved. At Brumadinho, recovery efforts from the 2019 tailings collapse continue, while neighboring operations are unaffected, potentially filling production shortfalls.⁷¹ These examples show how disasters expand brownfielding into areas of impact that intensify rather than dismantle the mining frontier. Instead, sunk capital, industrial clustering, and the ongoing demand for minerals create conditions where even catastrophe can become an example of brownfield mining.

Closure deferral and regulatory limitations

Finally, while scientists advocate for improved environmental impact assessments, most regulatory systems focus on “front-end” project approval processes, with less attention given to the latter phases of mine life.^{31,72} Once a mine is approved and permitted, expansion tends to proceed as a routine feature of the operational phase, even when changes materially transform the original risk and impact profile of a project.^{31,73} In this context, expansions tend to advance without the level of assessment or public consultation as the approval phase, especially when changes occur within existing lease areas. Mine closure plans routinely lag behind expanding disturbance, and financial assurance mechanisms (where they exist) often remain tied to the original project scope.⁷⁴ In effect, brownfielding becomes a mechanism for delaying rehabilitation and final closure that intentionally reduces the cost of brownfielding by postponing expenditure on closure costs. In an era where the acceleration of mining approvals is becoming a priority of mineral-endowed states,⁷² these issues constitute a deepening structural tension.

Some change is being driven at the local level, with communities demanding more of a say in expansion activities. Alcoa in Western Australia is one such example, where a bauxite

mine extension just 100 km from Perth and near significant jarrah forests received a record number of submissions to state approval authorities.¹⁶ However, more remote or vulnerable populations do not tend to have this kind of power. The uneven capacity to challenge mine expansion and the incremental nature of land-use change see brownfielding often advancing most readily in places that are least able to influence outcomes, reinforcing existing patterns of vulnerability and inequality,⁷⁵ including in the name of the “green” energy transition.⁷⁶

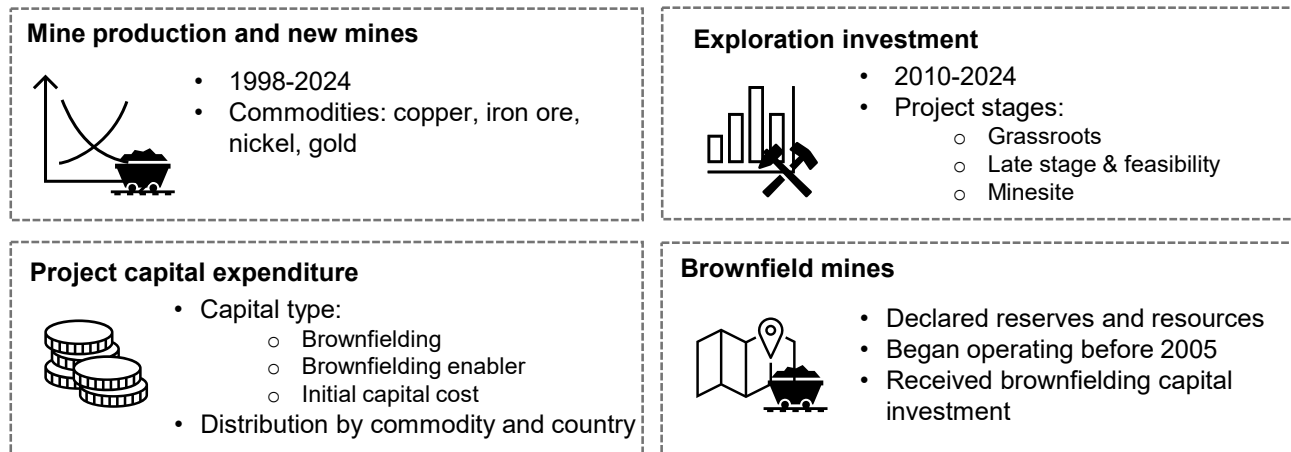
Future research

Our findings point to several urgent priorities for research and policy innovation. First, longitudinal tracking by companies or regulators of cumulative impacts remains weak, despite technical advances that could support it.⁷⁷ While mine footprint extents can be mapped with continuous, multi-decadal records, current approaches do not yet support precise, routine analysis of mine expansion, such as growing waste dumps and elevation changes in engineered tailings storage facilities. Global-scale monitoring of terrain change using digital elevation models remains limited, with coverage available only for selected years.^{78,79} Developing this capacity, and requiring operators to enable real-time, open-access spatial monitoring, is necessary for mining’s footprint and effects to become more visible and governable.

Second, developing a typology of brownfielding strategies is essential. The ability to draw clearer distinctions between, for example, surface and sub-surface expansion, vertically accumulating waste, and the temporal extension of mine life (including in the absence of physical expansion) carry different technical, regulatory, social, and environmental implications. Without a typology, governance frameworks remain blind to the intricacies of this growing phenomenon. Brownfield mining is increasingly sustaining the supply of minerals through regulatory systems that no longer match the scale, complexity, or character of mining’s long-term social and environmental risks. Such typologies could shift analysis away from treating brownfielding as business as usual and toward assessing the capacity of host contexts to cope with ongoing industrial change.⁸⁰ Better understanding of the link between typologies of brownfield mining and associated social and environmental change could help to trigger strategic reviews or other interventions, including new studies and opportunities for affected people to renegotiate underlying agreements, including those with Indigenous rights holders. Without agreed triggers, brownfielding could lock mining territories into deeper patterns of resource extraction that outpace institutional capacity to govern. By analyzing brownfield mining within its host context, future research could generate a clearer picture of how production and expansion interact with sociopolitical, ecological, and regulatory systems.

Third, there is a pressing need for deeper analysis of the policy and market drivers that are entrenching brownfielding as a strategy for securing the future supply of energy transition and critical minerals. Incentives such as capital availability, streamlined permitting, and national strategies are reinforcing a preference for reinvestment over discovery, even as states announce schemes to incentivize greenfield exploration and project development. Understanding how these factors operate and interact across commodities, companies, and country contexts, including by conducting grounded work in jurisdictions where capital

Step 1. Temporal trends and spatial patterns of capital investment in brownfield mining



Step 2. Spatial embeddedness and contextual conditions of brownfield mines

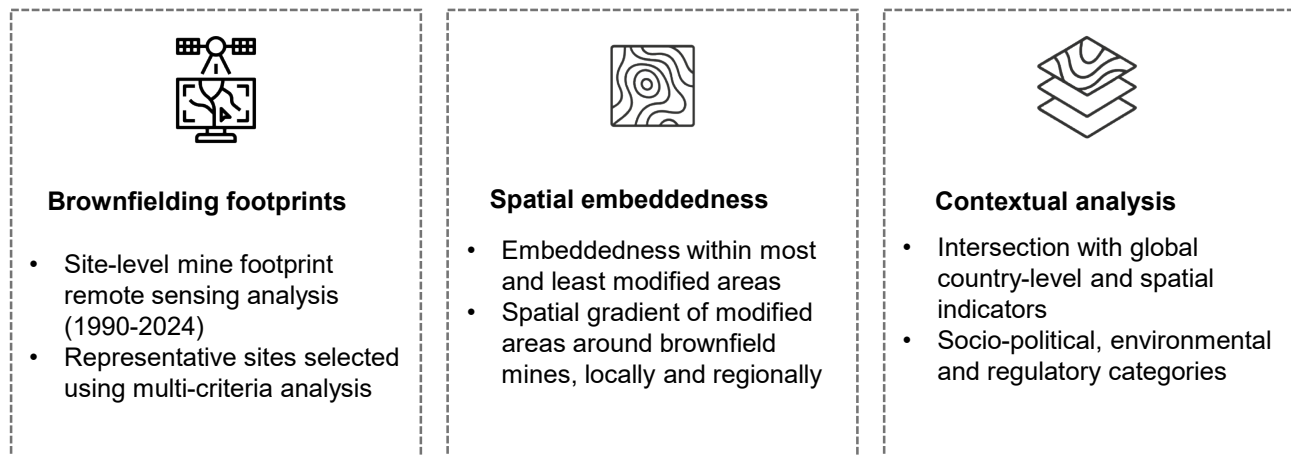


Figure 8. Methodological sequence

Step 1 involves analysis of temporal trends and patterns of mine production, exploration investment, project-based capital investment, and brownfield mines. Step 2 involves analysis of site-level mine expansion, spatial embeddedness within modified landscapes, and analysis of contextual conditions of brownfield mining.

expenditure data are limited (e.g., China), would support a more informed approach to research, reform, and local-level advocacy.

Brownfielding extends mining's frontier across time and space, amplifying social and environmental liabilities in ways that resource governance and regulatory systems are failing to contain. Approaching brownfield mining as a deepening structural feature of global mineral supply is essential if governance frameworks are to confront the systemic social and environmental liabilities that it generates.

METHODS

The methodological sequence involved two steps: (1) analyzing brownfielding temporal trends and spatial patterns and (2) conducting spatial and contextual analysis (Figure 8). Limitations are noted in each sub-section.

Brownfielding temporal trends and spatial patterns

Mine production data were obtained from the US Geological Survey's Mineral Commodity Summaries⁴² for the period 1998–2024 and refer to contained metal, noting that mine production is the most robust predictor of mine footprint size.⁵⁰ Data on the annual counts of new mines were sourced from the S&P Metals & Mining Properties database⁴³ using each site's recorded start-up year. Start-up year data are available for 63.7% of operating iron ore mines, 56.2% of nickel, 50.4% of copper, and 48.2% of gold (as presented in the table in Note S1). While the S&P database has limitations (e.g., it lacks production data for many historic, abandoned, and illegal operations, in particular, in geographies with inadequate reporting⁸¹), it remains the most comprehensive global dataset with project details beyond mine extent.

Exploration budget data were obtained from S&P.¹⁹ The analysis focused on the structure and trends in mineral exploration investment based on project stage, location, and commodity (data for iron ore are not available). We used S&P project stages for exploration purposes: (1) “grassroots,” or the earliest exploration stages, where no mine or known significant deposit exists, ranging from exploratory drilling to initial resource quantification; (2) “late stage & feasibility,” or further delineation of ore bodies and feasibility studies aimed at production decisions; and (3) “minesite,” or exploration activities conducted at or near existing mines or within economically viable transportation distances. Figures are presented for major mining companies, defined as listed companies with at least \$500 million in mining-related revenue and capable of developing a major mine.

To develop the dataset on brownfielding capital and sites, we used the S&P capital expenditure database.¹⁹ The selection included industrial minerals extracted in large quantities (iron ore, copper, bauxite, manganese, nickel, etc.) as well as precious and technology minerals, such as lithium, gold, cobalt, rare earth, etc. Coal and uranium were excluded. Downloaded data included 5,737 mine sites in the post-construction stages. The data were then filtered to exclude mines with no record of remaining reserves and resources and no record of capital expenditure, resulting in 1,467 sites. The data were further filtered to exclude mines that began production before 2005 to capture sites with established infrastructure and sunk capital, resulting in 583 sites. The reporting of capital expenditure varies across countries, ranging from 89.7% of mine sites in Chile to 24.2% in China, with a global average of 64.8% (see the table in [Note S3](#)). Therefore, cross-country comparisons may be affected by inconsistent data coverage and reporting practices, and our results might represent an underestimation of actual capital expenditure levels. Moreover, our analysis does not capture all brownfielding activity globally, as mines that commenced production after 2005 may also have been expanding, such that our approach may underestimate the scale of brownfield mining.

The next step was to identify mine sites with “brownfielding” capital expenditure. We defined “brownfielding” capital as expenditure that expands existing mines in space (physical expansion) and in time (prolonging the lifetime). The following capital cost categories were deemed to satisfy these criteria: “expansion,” “mine-life extension,” “new zone development,” “reopening” (after suspension), and “optimization.” These are different from “initial capital costs” required to start the mine up and from costs associated with “sustaining capital” and “major purchases” for maintaining and renewing existing operations, which we categorized as “brownfielding enabler” capital costs. The data were filtered to include sites with the “brownfielding” capital costs, resulting in 366 sites covering 58 countries and 16 commodities (bauxite, cobalt, copper, gold, iron ore, lanthanides, lithium, manganese, molybdenum, nickel, niobium, platinum, silver, tantalum, tin, and zinc).

Spatial and contextual analysis

Changes in mining footprint extents were mapped using time-series satellite imagery from 1990 to 2024. For each year, Landsat imagery with 30-m resolution was used to ensure temporal consistency. Four specific years were selected based on visually significant changes. Cloud-free mosaics were generated in Google

Earth Engine using a cloud-filtering algorithm, and final composites were created by computing the median pixel value for the whole year, allowing reliable interpretation in areas with frequent cloud cover. Digitization began with the most recent year (2024) to take advantage of clearer imagery, supported by high-resolution Sentinel-2 data as reference. The 2024 boundary served as the baseline, with earlier years digitized by adjusting vertices to match historical change. [Note S4](#) provides further details on the method.

Six mine sites were selected from the global dataset of 366 brownfielding operations. The sites—Turquoise Ridge (part of Nevada Operations), Mt. Tom Price (part of Hamersley Consolidated), Mogalakwena, Porgera, Sepon, and Voisey’s Bay—were chosen to reflect diversity in commodity type, geographic location (country, continent, and Köppen climate zone), investment scale, and the visibility of spatial expansion in satellite imagery (see the second table in [Note S4](#)).

The spatial embeddedness analysis focused on the degree to which brownfield mine sites are situated within modified landscapes. We developed a global spatial layer of frontier geographies to reflect the contrasting extents of human-induced land alteration and environmental intactness globally. The spatial layer was created by integrating four existing spatial layers. First, Köppen-Geiger climatic zones⁸² were used to establish environments least conducive to intensive land use by humans. Second, the human modification index (HMI)⁵³ was used to reflect the presence of infrastructure, industrial sites, and urban development. Cropland⁸³ and pastoral lands⁸⁴ were added to capture the extent of modification due to agriculture.

Least-modified areas encompass approximately 56 million km² (42.1% of the total land area, excluding Antarctica), while the spatial extent of most-modified areas covers 77 million km² (57.8%). This classification results from thresholds representing the highest level of practical convergence—identified using sensitivity analysis—between most- and least-modified areas across selected datasets (HMI 30%, no cropland presence and 7.5% or less pastureland per square kilometer). The spatial layer is visualized through a publicly available Google Earth Engine map,⁸⁵ allowing users to engage with individual thematic layers and adjust thresholds dynamically. Refer to [Note S5](#) for a more detailed description of the method and its limitations.

To quantify how brownfield mines are spatially embedded within modified landscapes, we depicted the share of highly modified land areas at increasing distances from each site. The method captures land-use dynamics across several spatial scales: the immediate “mine-site” zone (within 5 km), the “local” (25 and 50 km), and the broader “regional” context (75 and 100 km).

The final part of the analysis focused on understanding the contextual conditions in which brownfielding is occurring. Building on prior approaches of a similar nature,^{49,61} the method applied a spatial overlay of the 366 brownfield mines with thematic indicators derived from globally recognized spatial and country-level datasets. [Table 1](#) provides a description of the indicators, rationale for their selection, data sources, and indicator thresholds. Nine indicators were grouped into three categories. The “sociopolitical” category serves as a proxy for societal stability and inclusion, encompassing indicators for education, inequality, grievance, and peace. The “environmental” category reflects the ecological context, including indicators for water stress and proximity to areas of high biodiversity and protected

Table 1. Sociopolitical, environmental, and regulatory indicators: Description, rationale, sources, and high-risk thresholds

Indicator	Description	Rationale	Source	High-risk indicator threshold
Sociopolitical				
Education	measures average years of schooling, with the education of current and future generations receiving equal weights	impacts employability and informed public participation	UNDP Human Development Report ⁸⁶	8 years and below
Inequality	measures structural inequality that is based on group, education, economic status, or region; also considers perceptions of inequality and accounts for the opportunities for groups to improve their economic status	high inequality can fuel tensions over who benefits and who bears the costs	Fragile States Index E2: Economic Inequality ⁸⁷	5 and above
Grievance	focuses on divisions between different groups in society, particularly based on social or political characteristics, and their role in access to services or resources and inclusion in the political process	past group grievances make conflict more likely	Fragile States Index C3: Group Grievance ⁸⁷	5 and above
Peace	measures peace as the “absence of violence and absence of the fear of violence”; the index uses indicators classified under three themes: (1) ongoing domestic and international conflict, (2) societal safety, and (3) security and militarization	signals a greater risk of violence and instability	Global Peace Index ⁸⁸	2.372 or above
Environmental				
Baseline water stress	measures the ratio of water withdrawals to available renewable surface and groundwater at the catchment scale, indicating competition among users	scarce water increases competition between different land uses	World Resources Institute’s Aqueduct Water Risk 4.0 ⁸⁹	extremely high and arid and low water use

(Continued on next page)

Table 1. Continued

Indicator	Description	Rationale	Source	High-risk indicator threshold
Proximity to biodiversity and protected areas	measures distance to areas with high biodiversity or protected at the international, national, regional, or local scale	sites near important ecosystems face risks of lasting environmental harm	Key Biodiversity Areas 2024 ⁹⁰ and The World Database on Protected Areas (WDPA) 2023 ⁹¹	20 km and below
Regulatory				
Control of corruption	captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as “capture” of the state by elites and private interests	risks of bribery and opaque decision-making	Worldwide Governance Indicators ⁹²	defined by dataset authors: score equal to or below 0
Regulatory quality	captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development	affects implementation of permitting and enforcement	Worldwide Governance Indicators ⁹²	defined by dataset authors: score equal to or below 0
Freedom of the press	provides a measure of the media freedom situation based on an evaluation of pluralism, independence of the media, quality of legislative framework, and safety of journalists in each country	risks of constrained independent scrutiny and reporting and undetected community abuses	Reporters Without Borders ⁹³	55.2 or below

regions. The “regulatory” category represents the effectiveness of institutional frameworks and governance mechanisms, incorporating measures of control of corruption, regulatory quality, and freedom of the press. Indicator thresholds were applied to indicate mine sites located in contexts with high risk. While the indicators may serve as imperfect proxies for the issues of interests, they nonetheless highlight important patterns and challenges that warrant further analysis.

RESOURCE AVAILABILITY

Lead contact

Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Deanna Kemp (d.kemp@uq.edu.au).

Materials availability

The global spatial layer of the world’s frontier geographies is visualized through a publicly available Google Earth Engine map available at <https://ee-frontend.projects.earthengine.app/view/frontier-geographies>.⁸⁴

Data and code availability

Data and code have been deposited at The University of Queensland’s Data Collection and are publicly available at <https://doi.org/10.48610/207ff37> and <https://doi.org/10.48610/7965558> as of the date of publication.

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AUTHOR CONTRIBUTIONS

Conceptualization, D.K., J.L., and J.R.O.; data curation, J.L., A.M.L., M.L.E.A., R.A.K., and M.R.U.S.; formal analysis, D.K., J.L., and J.R.O.; funding acquisition, D.K. and J.R.O.; investigation, D.K., J.L., M.L.E.A., C.U., and J.R.O.; methodology, D.K., J.L., A.M.L., M.L.E.A., and J.R.O.; project administration, D.K.; resources, D.K.; software, J.L. and M.L.E.A.; supervision, D.K., J.L., A.M.L., and J.R.O.; validation, J.L., M.L.E.A., C.U., and J.R.O.; visualization, J.L., A.M.L., M.L.E.A., R.A.K., and M.R.U.S.; writing – original draft, D.K.,

J.L., and J.R.O.; writing – review & editing, D.K., J.L., A.M.L., M.L.E.A., C.U., A.B., and J.R.O.

DECLARATION OF INTERESTS

D.K. is a member of the *One Earth* advisory board.

SUPPLEMENTAL INFORMATION

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Supplemental information

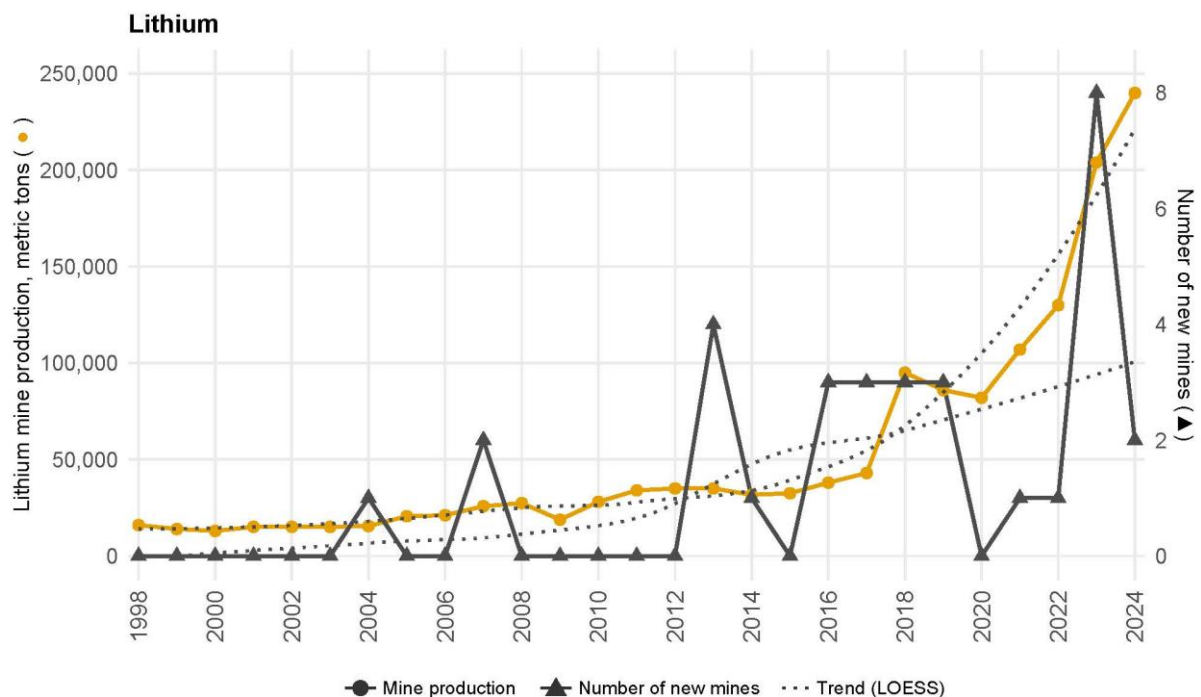
**The rise of brownfield mining is reshaping
global mineral supply and intensifying
social and environmental risk**

Deanna Kemp, Julia Loginova, Alex M. Lechner, Michelle Li Ern Ang, Riska A. Kuswati, Muhamad Risqi U. Saputra, Corinne Unger, Anthony Bebbington, and John R. Owen

Supplemental Information

Supplemental Notes

Note S1. Mine production and new mines



Lithium production over time and number of new mines that commenced production between 1998 and 2024. Trend lines created by applying LOESS (Locally Eliminated Scatterplot Smoothing). Data: USGS (2025)¹ and S&P Metals & Mining Properties database (2025)².

The figure above shows a steady rise in global lithium mine production from the late 1990s through mid-2010s, followed by a sharp acceleration after 2016 and especially after 2020. The number of new lithium mines beginning production each year fluctuates considerably, with noticeable spikes in 2007, 2013, 2017-2019, and 2023. This indicates uneven periods of new lithium project development. The LOESS trend line indicates the overall upward trajectory in both production volume and mine openings over the 1998-2024 period.

The table below provides an overview of mining project data categorised by primary commodity, focusing on number of projects in the dataset, mine openings and data completeness regarding start-up years. The table indicates that data completeness remains moderate, with start-up years reported by half of all mines on average. Across commodities, iron ore has the highest data completeness for reported start-up year at 63.7% of mines, while lithium has the lowest at 46.8%.

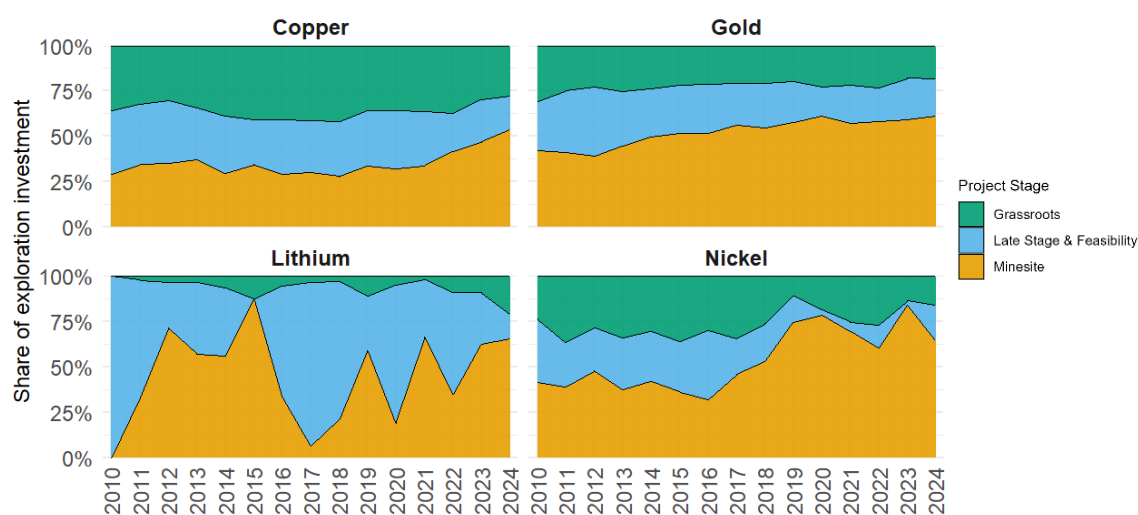
Reported start-up year of mines by commodity.

Primary commodity	Available projects	New mines opened since 1998	Reported year of mine start up	Percentage of mines with reported start-up year
Copper	992	345	500	50.4%
Gold	2,704	878	1,304	48.2%
Iron ore	1,127	537	718	63.7%
Lithium	79	32	37	46.8%
Nickel	242	97	136	56.2%

Data: S&P Metals & Mining Properties database (2025)².

Note S2. Mineral exploration investment

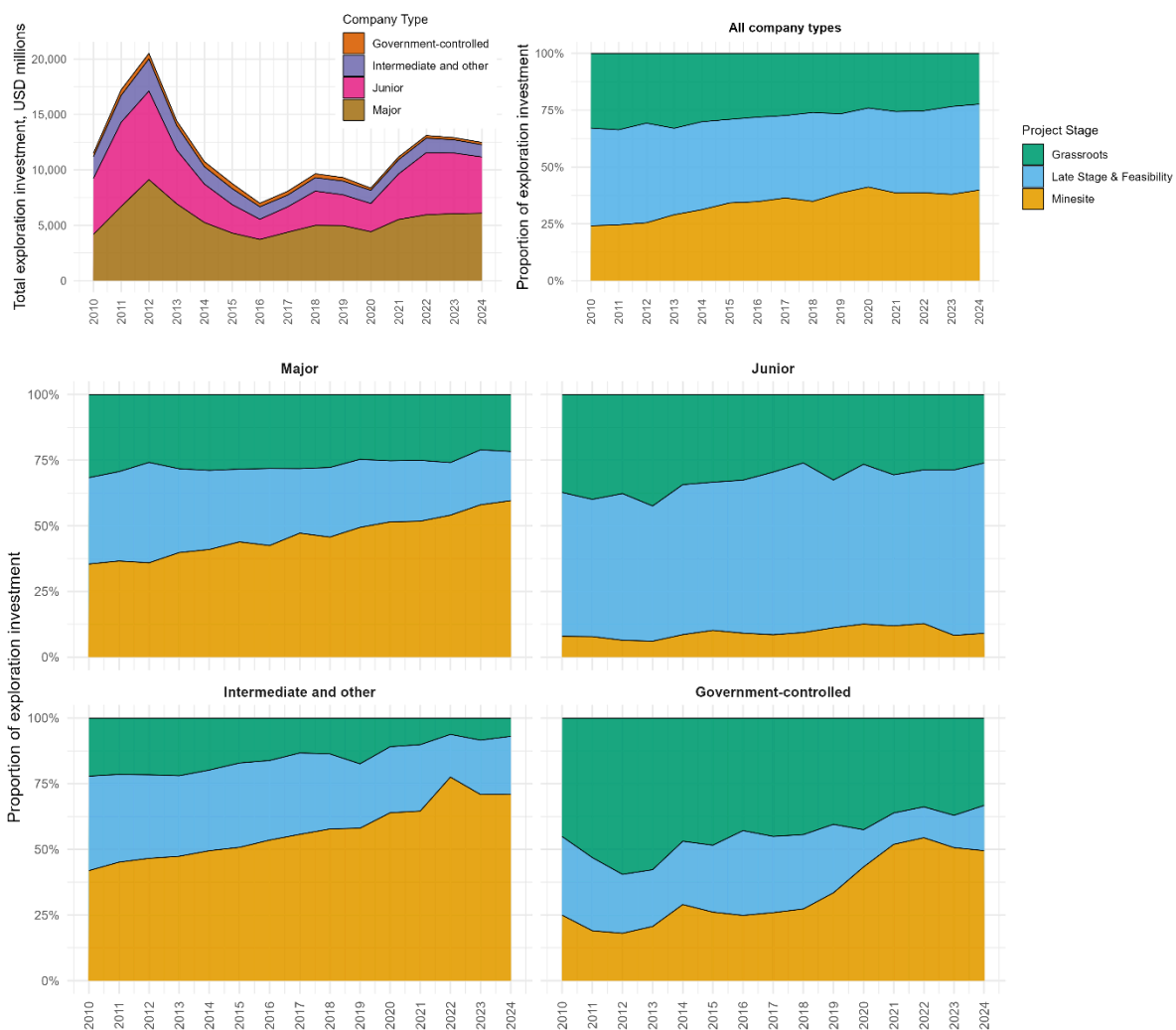
The figure below presents trends in exploration investment from 2010 to 2024 by project stage and commodity. Across copper, gold and nickel, “minesite” exploration increasingly dominates, indicating that the majority of investment is directed toward expanding or sustaining existing operations rather than discovering new deposits. For these commodities, “Grassroots” exploration shows a general decline over time, especially pronounced in gold and copper. “Late stage & feasibility projects” stage maintains a steady share, particularly for copper and gold, reflecting ongoing project development and evaluation activity. In contrast, lithium shows year-to-year fluctuations, highlighting its volatility in response to market demand for battery materials.



Global exploration investment by project stage and commodity. Data: S&P Metals & Mining database (2025)².

The figure below presents trends in exploration investment from 2010 to 2024 across project stages and company types, using both absolute (top left) and proportional (rest) measures. In this period, peak investment occurred around 2012, led primarily by major and junior companies. A sharp decline followed, bottoming around 2016, with partial recovery from 2017, and another substantial increase from 2020. From 2022, global exploration investment has stagnated. Major companies consistently maintain a significant share of total investment, accounting for 48.8% of total exploration investment in 2024.

Across all company types, “minesite” exploration has steadily increased, in 2024 accounting for nearly 40% of investment. “Grassroots” exploration has declined over time, from 32.9% of total investment in 2010 to 22.4% in 2024. “Late stage & feasibility” remained stable but gradually decreasing in share (from 43.0% to 37.8% between 2010 and 2024).



Global exploration investment by company type and project stage. Data: S&P Metals & Mining database (2025)².

Across major companies, there has been a strong shift toward “minesite” exploration, rising from approximately 35% in 2010 to over 60% by 2024. “Late stage & feasibility” exploration declined the most, from 32.9% in 2010 to 18.7% in 2024. Exploration investment by junior companies are dominated by “late stage & feasibility”, accounting for 64.9% in 2024, an increase from 54.8% in 2010. Investment in “minesite” exploration has been increasing until 2022, followed by a slight decline. Intermediate-sized and government-controlled companies account for significantly less contribution to exploration investment, yet also exhibiting a shift towards “minesite” exploration, mostly noticeable from 2019. For both company types, “minesite” exploration dominates the exploration portfolio, accounting for 71.0% and 49.5% accordingly.

Note S3. Capital investment flows in brownfield mines

The table below shows the distribution of brownfield mining capital across major mining countries. It shows that as of 2024, there were 898 mines globally that commenced operating in 2005 or earlier, of which 64.8% had reported capital expenditures. Chile leads with the largest share of global brownfielding capital (74.3 billion USD, or global share of 25.2%), reported by 35 of its 39 mines (89.7%), and an average brownfield capital of USD 2.5 billion per mine. This is followed by USA and Australia, contributing 11.4% and 10.1% of the global total, respectively. Although Indonesia has relatively fewer mines (13), it shows a high average brownfielding capital (USD 5.4 billion per mine). Canada, Peru, and South Africa each contribute between 5.9% and 6.6% of the total. The “Rest of the world,” despite a lower reporting rate (51.5%), accounts for 15.4% of global capital, while China’s share is modest (at 2.0%) with only 24.2% of mines reporting capital expenditure. Overall, only 64.8% of mines reported capital expenditure data, meaning over one-third of global mines have missing or unreported figures. This creates potential bias when countries with more complete reporting (like Chile or South Africa) may appear to have disproportionately higher investment intensity than those with poor reporting (like China).

Reporting of capital expenditure data by country.

Countries	Number of mines commencing in 2005 or earlier	Number of mines with reported capital expenditure	Share of mines with reported capital expenditure, per cent	Average brownfielding capital, billion USD	Total brownfielding capital, billion USD	Global share of brownfielding capital, per cent
Chile	39	35	89.7%	2.5	74.3	25.2%
USA	88	60	68.2%	1.2	33.6	11.4%
Australia	81	58	71.6%	0.9	29.7	10.1%
Indonesia	13	11	84.6%	5.4	26.9	9.1%
Canada	43	37	86.0%	0.9	19.6	6.6%
Peru	43	36	83.7%	1.0	19.4	6.6%
South Africa	52	46	88.5%	0.6	17.4	5.9%
Brazil	35	23	65.7%	0.9	11.2	3.8%
Russia	39	28	71.8%	0.7	10.7	3.6%
Mexico	32	25	78.1%	0.4	6.8	2.3%
Rest of the world	433	223	51.5%	0.4	45.4	15.4%
<i>China</i>	<i>198</i>	<i>48</i>	<i>24.2%</i>	<i>0.2</i>	<i>6.0</i>	<i>2.0%</i>
Total	898	582	64.8%	0.9	294.9	100.0%

Note S4. Site-level mine footprint remote sensing analysis

Changes in mine footprint extents were mapped using time-series satellite imagery from 1990 to 2024. Six mine sites were selected from the 366 brownfielding operations: Sepon (Laos), Mogalakwena (South Africa), Mt Tom Price (part of Hammersley Consolidated, Australia), Turquoise Ridge (part of Nevada Operations, USA), Voisey's Bay (Canada), and Porgera (Papua New Guinea).

The selection methodology employed multiple criteria, encompassing commodity diversification, geographical distribution across different countries and continents with Köppen climate classifications, investment magnitude, and the detectability of temporal changes through satellite remote sensing. Given the database's investment distribution spanning \$0 to \$23.6 billion with a mean of \$60 million and investment frequency ranging from 0 to 20 instances per site with an average of 6.1, we incorporated sites representing both high-capital ventures exceeding the population mean (exemplified by Turquoise Ridge and Mt Tom Price) and lower-investment operations below the mean (such as Sepon).

Changes in mine extents were mapped using time-series satellite imagery to capture major development phases while minimising redundancy. Four representative years from 1990 to 2024 were selected for each site based on visual inspection using Google Earth Engine Timelapse. These years were chosen to reflect clear temporal changes in surface expansion, forming the basis for subsequent digitisation and analysis.

To ensure consistent data quality across the 34-year period, a multi-sensor Landsat approach was adopted within Google Earth Engine. Landsat 5 Thematic Mapper (TM) served as the primary source from 1990 to 2012, while Landsat 7 Enhanced Thematic Mapper Plus (ETM+) was incorporated from 1999 onward to enhance temporal coverage. Despite the Scan Line Corrector (SLC) failure in 2003, SLC-off data were retained due to their preserved radiometric and geometric integrity. For the post-2013 period, Landsat 8 Operational Land Imager (OLI) provided improved radiometric performance and acquisition frequency. Cloud-free mosaics were generated using a cloud-filtering algorithm, and annual composites were produced by calculating the median pixel value across all valid images, improving interpretability in regions with frequent cloud cover. A summary of yearly image availability is provided in the first table presented below.

Footprint delineation was conducted manually for each selected year. The process began with the most recent observation year (2024), using Landsat 8 composites as the primary input, refined where necessary with Sentinel-2 imagery to improve spatial accuracy. This 2024 boundary served as a geometric reference for earlier years. For each prior observation, the 2024 polygon was duplicated and adjusted only where visual inspection showed change, ensuring topological consistency across the time series. This backward digitising approach minimised spatial misalignment and ensured that interannual area differences reflected actual land cover change rather than delineation error. The mine area values along with the profiles of selected brownfield mining sites are shown in the second table presented below.

Annual image availability status for selected sites (1990–2024).

Year	Mogalakwena	Voisey's Bay	Turquoise Ridge (part of Nevada Operations)	Mt Tom Price (part of Hamersley Consolidated)	Sepon	Porgera
1990	Green	Blue	Green	Green	Green	Blue
1991	Green	Green	Green	Green	Green	Green
1992	Green	Green	Green	Green	Green	Green
1993	Green	Green	Green	Green	Green	Green
1994	Green	Blue	Green	Green	Green	Green
1995	Green	Green	Green	Green	Green	Blue
1996	Green	Blue	Green	Green	Green	Green
1997	Green	Blue	Green	Green	Green	Blue
1998	Green	Green	Green	Green	Green	Blue
1999	Blue	Green	Green	Green	Blue	Blue
2000	Green	Green	Green	Green	Green	Blue
2001	Green	Green	Green	Green	Green	Green
2002	Green	Green	Green	Green	Green	Green
2003	Green	Green	Green	Green	Green	Blue
2004	Green	Green	Green	Green	Blue	Blue
2005	Green	Green	Green	Green	Green	Blue
2006	Green	Green	Green	Green	Green	Blue
2007	Green	Green	Green	Green	Green	Blue
2008	Green	Green	Green	Green	Green	Green
2009	Green	Green	Green	Green	Green	Green
2010	Green	Green	Green	Green	Green	Blue
2011	Green	Green	Green	Green	Green	White
2012	Green	Green	Green	Green	White	White
2013	Green	Green	Green	Green	Green	Blue
2014	Green	Green	Green	Green	Green	Green
2015	Green	Green	Green	Green	Green	Green
2016	Green	Green	Green	Green	Green	Green
2017	Green	Green	Green	Green	Green	Blue
2018	Green	Blue	Green	Green	Green	Green
2019	Green	Green	Green	Green	Green	Green
2020	Green	Green	Green	Green	Green	Green
2021	Green	Green	Green	Green	Green	Green
2022	Green	Green	Green	Green	Green	Green
2023	Green	Green	Green	Green	Green	Green
2024	Green	Blue	Green	Green	Green	Green

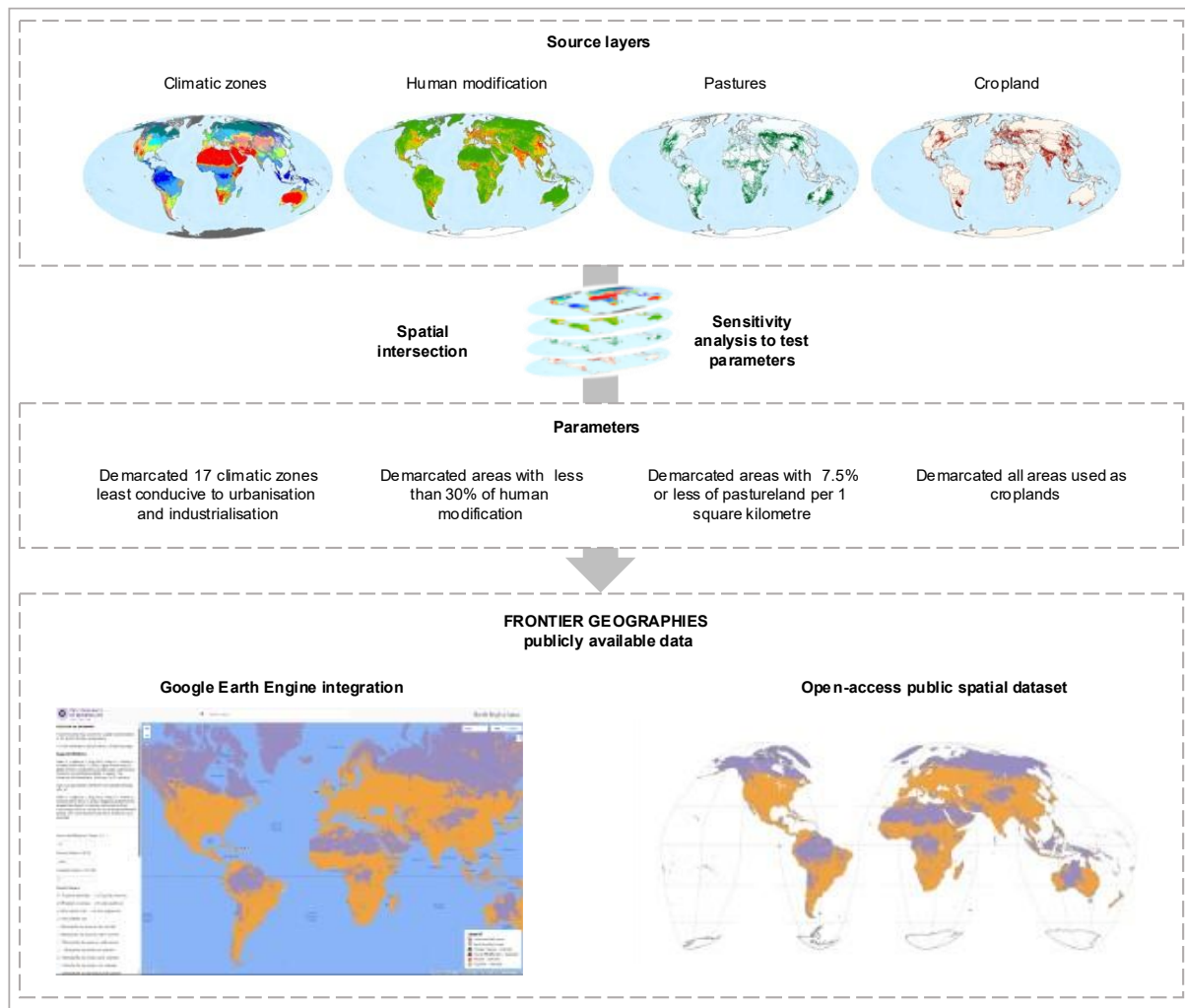
	Clear image — Good quality images available (low cloud cover below 30%)
	Most cloudy — Images available but mostly cloudy (>30% cloud cover)
	No image — No valid imagery available for the year

Overview of selected brownfield mining sites.

Site name	Location	Primary commodity	Climate classification	Total capital investment, billion USD	Year	Area (km ²)
Sepon	Laos	Copper	Tropical	0.398	2005	4.60
					2008	10.20
					2013	17.60
					2024	23.50
Mogalakwena	South Africa	Platinum	Arid	3.998	1993	0.75
					2007	20.30
					2014	33.03
					2024	35.74
Mt Tom Price (part of Hamersley Consolidated)	Australia	Iron Ore	Arid	11.838	1990	17.14
					2003	22.19
					2015	28.97
					2024	29.78
Turquoise Ridge (part of Nevada Operations)	USA	Gold	Arid	14.067	1990	26.68
					2001	48.21
					2014	52.07
					2024	53.15
Voisey's Bay	Canada	Nickel	Cold	6.681	2003	2.02
					2010	3.37
					2017	4.24
					2024	4.75
Porgera	Papua New Guinea	Gold	Temperate	2.658	1991	0.40
					2001	10.70
					2015	13.40
					2024	14.40

Note S5. Spatial embeddedness

A global map of frontier geographies was created to depict the world's most and least modified terrestrial areas, as shown in the figure below. To represent frontier areas, we used the following source layers: 1) climatic zones; 2) cumulative human modification; 3) extent of croplands; and 4) extent of pastures. Parameters were established to indicate the extent to which human activities have altered lands globally. Our approach supports customisable thresholding for other users through Google Earth Engine³.



Methodological approach.

Selection of layers and parameters

Climatic zones were assessed using global maps of the Köppen-Geiger climate classification at high 1-km resolution (version 2) for the period 1991–2020⁴. First developed in the 19th century, this climate classification aggregates complex climate gradients and has been extensively used. We identified zones (17 out of 30) that have been less conducive to urbanisation and industrialisation. To further identify lands with low levels of human alteration, a cumulative measure of human modification of terrestrial lands (HMI) was used that models

13 different stressors from 5 main categories: electrical infrastructure, mining and energy production, transportation, agriculture, and human settlement⁵.

Scaling and back-testing were used to optimise the parameters based on the highest level of practical convergence across a multitude of mainstream data sources. A sensitivity analysis (see below) was conducted using established break-points differentiating concentration of population density, terrestrial land use, land intactness and level of human pressures and modification. Based on the results of a sensitivity analysis, a threshold of 30% HMI was applied to demarcate areas with low levels of cumulative human modification, capturing about 80% of areas with low and medium modification⁵. Further, lands used for croplands and pastures were demarcated to capture lands modified by agriculture that were not picked up by the HMI thresholding of 30%. The unified cropland layer⁶ was used to demarcate lands dedicated to agriculture (no cropland threshold). A threshold of 7.5% or less pastureland per 1 square kilometre of the global pastures layer from the Global Agricultural Lands collection⁷ was used to demarcate areas with significant levels of animal grazing, as some tribal peoples' livelihoods depend on livestock. Before any processing, all spatial layers were projected to the Goode equal-area homolosine projection using WGS84 datum. Raster files were re-sampled to the highest resolution of 1 square kilometre. The analyses have been performed in ArcGIS Pro (version 3.1.0) and R (version 4.3.1). The final dataset is presented in an interactive Google Earth Engine App³.

Limitations

The most recent and widely used global and open-sourced datasets were sourced for each indicator. In sourcing these datasets, we recognize their underlying limitations regarding inconsistency, omission, and inaccuracy. These limitations are well established. The accuracy of the climatic zones during the 1991 to 2020 period, for example, is affected by climate change and requires further data validation in certain regions such as mountainous and tropical areas. A related consideration is the significant local and regional variability within regions. The incompleteness of input infrastructure data used to create the HMI was also highlighted by the authors of the dataset. In addition, identifying global and regional-scale pasture and croplands, among other mixed used land use classifications, persists as a definitional challenge. For each dataset used in our study, the original authors reported the limitations of the data following robust testing and accuracy assessments which we believe is sufficient to justify fitness for use.

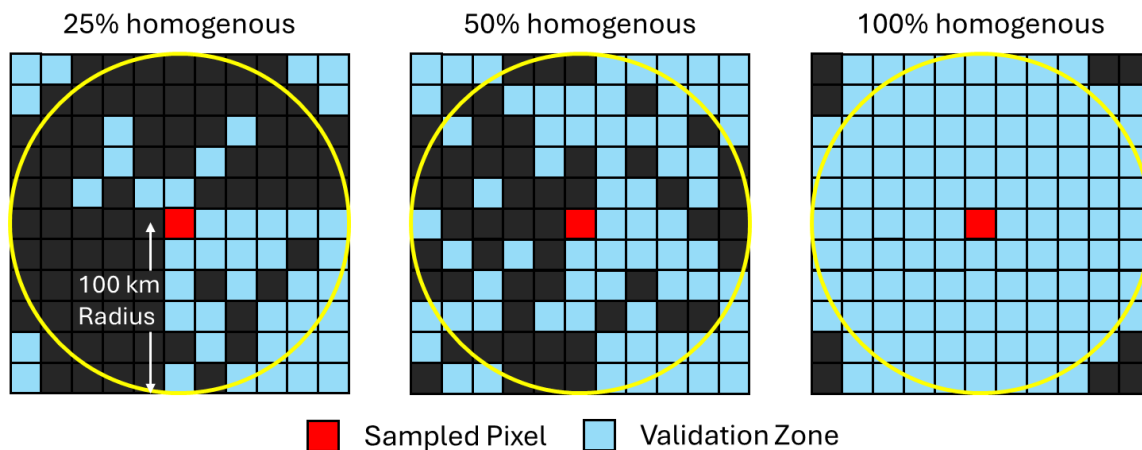
Sensitivity analysis

The sensitivity analysis used to determine optimal threshold values for delineating the least and most modified areas. The method included three steps: (1) establishment of spatial validation zones (2) generation of random points within validation zones, (3) calculation of percentage overlap of validation points with areas identified as least and most modified. These steps were applied to five thresholds listed in the second table listed below.

First, validation zones were created for the least and most modified areas using existing global spatial datasets. The datasets used for validation are independent from the datasets used to generate the spatial representation of frontier geographies. This avoids spatial autocorrelation. To establish least modified validation zones, intersections were identified using the following

thresholds: (1) population density of less than 300 people per square kilometre^{8,9}, (2) closed forest, bareland, snow and ice, herbaceous wetland, as well as moss and lichen land cover¹⁰ and (3) Human Footprint index value less than or equal to 10 which is considered to represent ‘Wilderness’¹¹. To establish most modified validation zones, major cities and high-intensity cropland areas were identified using the intersection between (1) urban and high-density population clusters of more than 300 people per km^{8,9}, (2) agriculture, urban and built-up land cover¹⁰, and (3) areas with human pressures of more than 10 on the Human Footprint Index¹¹.

Second, validation points were randomly generated within the validation zones to prevent sample selection bias. The two types of validation zones – for the least and most modified areas – demonstrate two divergent forms of land cover. The former has large areas with high levels of homogeneity while the latter is characterised by high levels of spatial fragmentation. Hence, a criterion of 100% homogenous pixels within a radius of 100 kilometres (the first table shown below) was used for sampling within the least modified validation zones. This ensures that random validation points are only sampled within fully homogenous validation zones (the figure below). Out of 1000 pixels sampled, 231 validation points fulfilled these criteria and were used to conduct the sensitivity analysis. Since the validation zones for the most modified areas are largely heterogeneous and fragmented, a 25%-pixel homogeneity within a radius of 100 kilometres was used with a greater number of pixels sampled (n=10,000) to obtain 118 validation points (the first table below).



The level of validation zone homogeneity within the 100km buffer area (yellow circle) around the sampled pixel (red) was set as the criteria to minimize the likelihood of stray pixels being included as validation points for the sensitivity analysis.

Criteria used to randomly generate points within validation zones.

	Radius of circle (km) of buffer zone	Criteria: Pixel homogeneity within buffered zones (%)	Total number of pixels sampled	Number of validation points generated
Least	100	100	1,000	231
Most	100	25	10,000	118

Finally, percentage overlap between validation points and least and most modified areas was calculated. The percentage overlap was used to cross-examine five sets of thresholds for the least and most modified frontier geographies (the table below). By calculating the threshold step change and the rate of change of the moving average of the percentage of overlap between the least and most modified validation points, we determined that Threshold 2 produced the highest level of test coherence when compared to the margin of other thresholds.

Sensitivity analysis results to determine the most optimal threshold (Threshold 2 – highlighted in grey) for the least and most modified frontier geographies.

	Indicators			Percentage overlap (%) of validation points		Threshold step change		ROC*
	HMI	Cropland	Pastures	Least modified areas	Most modified areas	Least modified areas	Most modified areas	
Threshold 1	0.1	0	0.025	76.53	99.81	<i>NA</i>	<i>NA</i>	0.011
Threshold 2	0.3	0	0.075	88.00	99.78	11.47	-0.03	0.022
Threshold 3	0.5	0.1	0.125	89.61	98.71	1.61	-1.07	0.000
Threshold 4	0.7	0.14	0.175	90.41	97.82	0.80	-0.89	-0.001
Threshold 5	0.9	0.18	0.225	90.78	96.80	0.37	-1.02	<i>NA</i>

*ROC refers to the rate of change of moving average of percentage overlap for least and most modified areas.

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